Transportation Research Part A 94 (2016) 255–265

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Development of destination choice models for pedestrian travel

Kelly J. Clifton [a,*], Patrick A. Singleton [a], Christopher D. Muhs [a,1], Robert J. Schneider [b]

[a] Department of Civil & Environmental Engineering, Portland State University, PO Box 751 – CEE, Portland, OR 97207-0751, United States
[b] School of Architecture & Urban Planning, University of Wisconsin – Milwaukee, PO Box 413, Milwaukee, WI 53201, United States

ARTICLE INFO

Article history:
Received 9 July 2015
Received in revised form 30 June 2016
Accepted 20 September 2016
Available online 29 September 2016

Keywords:
Walking
Pedestrians
Destination choice
Travel behaviors
Built environment
Active transportation

ABSTRACT

Most research on walking behavior has focused on mode choice or walk trip frequency. In contrast, this study is one of the first to analyze and model the destination choice behaviors of pedestrians within an entire region. Using about 4500 walk trips from a 2011 household travel survey in the Portland, Oregon, region, we estimated multinomial logit pedestrian destination choice models for six trip purposes. Independent variables included terms for impedance (walk trip distance), size (employment by type, households), supportive pedestrian environments (parks, a pedestrian index of the environment variable called PIE), barriers to walking (terrain, industrial-type employment), and traveler characteristics. Unique to this study was the use of small-scale destination zone alternatives. Distance was a significant deterrent to pedestrian destination choice, and people in carless or childless households were less sensitive to distance for some purposes. Employment (especially retail) was a strong attractor: doubling the number of jobs nearly doubled the odds of choosing a destination for home-based shopping walk trips. More attractive pedestrian environments were also positively associated with pedestrian destination choice after controlling for other factors. These results shed light on determinants of pedestrian destination choice behaviors, and sensitivities in the models highlight potential policy-levers to increase walking activity. In addition, the destination choice models can be applied in practice within existing regional travel demand models or as pedestrian planning tools to evaluate land use and transportation policy and investment scenarios.

1. Introduction

There have long been calls for research to improve our understanding of walking behaviors and to create better analytical tools to aid in planning for non-motorized modes. Such tools have the potential to inform infrastructure investments, quantify mode shifts, improve safety analyses, and create outputs relevant to emerging issues of public health, economic development, and sustainability. Despite recent increased interest in planning for walking, current forecasting tools—namely regional travel demand models—incompletely represent pedestrian behaviors (Singleton and Clifton, 2013). However, two recent advances have opened the door to significant innovations in pedestrian modeling: (1) the availability of spatially disaggregate travel behavior data (documenting walking trips more accurately); and (2) detailed data about the quality of the

* Corresponding author.
E-mail addresses: kclifton@pdx.edu (K.J. Clifton), patrick.singleton@pdx.edu (P.A. Singleton), cdm@dksassociates.com (C.D. Muhs), rjschnei@uwm.edu (R.J. Schneider).
[1] Present address: DKS Associates, 720 SW Washington Street, Suite 500, Portland, OR 97205, United States.

http://dx.doi.org/10.1016/j.tra.2016.09.017
0965-8564/

pedestrian environment (including pedestrian barriers and supports and fine-grained land use characteristics). Both advances allow pedestrian travel behaviors to be modeled at an appropriate scale.

Taking advantage of these data, recent research by the authors shows how four-step travel models can be improved to account for walking behaviors (Clifton et al., 2013, 2016). Our previous work identified factors associated with trip generation for pedestrian trips. This paper takes our work to the next stage—destination choice—and describes the development of pedestrian destination choice models, including behavioral influences, conceptual frameworks, model estimation results, policy implications, and planning applications.

Little research exists on the destination choice behaviors of pedestrians. Our paper contributes to this topic by including commonly-identified influences on destination choice from the broader literature along with spatial variables that account for the quality of the pedestrian environment. Measures developed here include elements of the environment that support walking and those that detract from walking. That is, this study focuses on destination choices for pedestrian travel, testing the influences on walking behavior at a scale appropriate for pedestrians, and includes relevant variables for pedestrian travel. It identifies measures, especially of the built environment, to which pedestrian behavior may be sensitive, highlighting potential policy-levers to increase levels of walking and physical activity. These behavioral sensitivities to distance, destination attractions, and the pedestrian environment can be useful for informing land use, urban design, and transportation policies, including policies related to carless households. Combined with previous work, our effort adds to the development a pedestrian planning tool that can be used to better estimate total walking activity in a given study area by combining data on trip origins and destinations.

The paper first provides background and context on the framework for four-step models to better represent walking activity. It then presents key concepts included in destination choice modeling along with methods and data. Model estimation results follow. The paper concludes with a discussion of the behavioral interpretations and policy-relevance of our findings, potential planning applications of the pedestrian destination choice models, study limitations, and opportunities for future work.

2. Background

A framework to better represent walking activity in travel demand models, introduced previously by the authors (Clifton et al., 2013, 2016), is illustrated in Fig. 1. The framework consists of four main steps, outlined below. Foremost, it increases the ability of regional travel models to represent walking within a trip-based structure without adding significant complexity or data requirements. It also has the potential to be modified to function as a standalone tool for pedestrian planning at a variety of scales, and the destination choice step in particular may be amenable for inclusion in activity based models.

1. Change the spatial unit of analysis for trip generation (all modes) from transportation analysis zones (TAZs) to pedestrian analysis zones (PAZs). Here, PAZs are uniform grid cells; in this application they have 264 ft (80 m) sides.
2. Apply a walk mode split model to estimate the number of walk trips produced in each PAZ. This binary logit model includes spatially disaggregate built environment and socioeconomic variables that measure relationships between walking and the physical environment.
3. Aggregate trips by vehicular modes (auto, transit, and bicycle) to the zonal structure of the regional model (TAZs) and then proceed with the remaining stages for these modes in the regional model.
4. In parallel procedure, apply a destination choice model to distribute the number of walk trips produced in each PAZ (step 2) to destinations.

Steps 1–3 have been described previously (Clifton et al., 2013, 2016). This paper focuses on the fourth step and describes the development of the pedestrian destination choice model.

3. Literature review

Trip distribution is the second step of traditional four-step travel demand models (Ortúzar and Willumsen, 2011). Historically, trip distribution methods include growth factor methods and gravity model methods. More recently, practice is moving towards using destination choice models to distribute trips from origins to probable destinations. Destination choice models can have a similar model structure to the multinomial logit (MNL) models often used for mode choice. (The traditional gravity model for trip distribution has been shown to be mathematically equivalent to an MNL model with two attributes: size and impedance (Anas, 1983).) Existing literature offers guidance for estimating destination choice models, especially with respect to choice set generation (Pagliara and Timmermans, 2009) and variable specification (Ben-Akiva and Lerman, 1985; Bernardin et al., 2009; Borgers and Timmermans, 1988; Pozsgay and Bhat, 2001). While choice sets could be constructed using deterministic rules or data on the perceived availability of alternatives (Ortúzar and Willumsen, 2011; Pagliara and Timmermans, 2009), most destination choice sets contain a sample of alternatives (Ben-Akiva and Lerman, 1985; Lemp and Kockelman, 2012). Destination choice model specifications typically include, at a minimum, terms for impedance (e.g., distance, generalized cost) and size (e.g., employment) (Ben-Akiva and Lerman, 1985; Bhat et al., 1998).

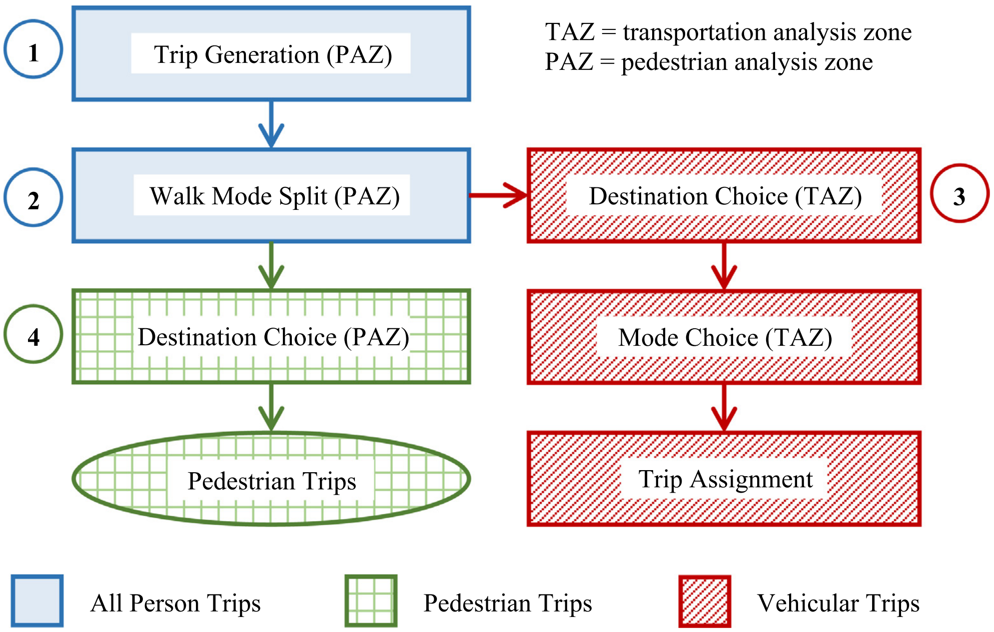

Fig. 1. Framework to increase representation of walking in conventional travel demand models (from Clifton et al., 2013, 2016).

It is important to consider the unique determinants of walking when investigating pedestrian destination choice behavior. Research has identified a common set of built environment features that affect walking. Distance to destinations is often a strong factor (Saelens and Handy, 2008). Walking has been positively associated with residential and employment density, land use mix, and connectivity (Ewing and Cervero, 2010; Saelens and Handy, 2008; Saelens et al., 2003), and may also be related to transit accessibility (Schneider et al., 2009) and street-level characteristics like sidewalks (Rodrıguez and Joo, 2004). Thus far, most studies have analyzed mode choice or walk trip frequency; few have looked solely at environmental correlates of pedestrian destination choice.

The current effort is unique since this is one of the first studies to focus on destination choice models for pedestrians distinct from other modes at a regional level. Some research lends insights to pedestrian destination choice behavior, with limitations. Borgers and Timmermans' (1986) study of pedestrian retail shopping trips found that trip distance and retail floor area had significant impacts on destination choice. However, the study was limited to a city center and did not test impacts of built environmental attributes. Eash (1999) found positive associations between a "pedestrian environment factor" (PEF) and destination choices in models of non-motorized trips in Chicago. However, the PEF variable was based solely on the number of census blocks in a sub-zone—only a rough measure of the pedestrian environment—making it difficult to draw conclusions about behavior and policy implications. Khan et al. (2014) developed destination choice models for non-motorized trips and explored effects of many built environment measures, but despite parcel-level data being used for sequential trip generation and mode choice models, TAZ-level data were used in the destination choice step. The TAZ is a less desirable unit for evaluating pedestrian trips, which tend to be short and therefore are mostly intrazonal in a TAZ system.

Based on the unique aspects of pedestrian behaviors and contributions of previous literature, our model development is guided by the following points:

- *Distance sensitivity*: Pedestrians are highly responsive to distance, so choice sets are constrained to local destinations based upon some threshold. Distance sensitivity likely varies by trip purpose.
- *Pedestrian supports*: Some built environment influences are unique to pedestrian travel, particularly when measured at a fine spatial scale around origins, destinations, and along the potential route. Existing destination choice studies test pedestrian environment variables that are coarse in either definition (Eash, 1999) or geographic scale (Khan et al., 2014), leaving room for improvement. For example, this study incorporates the pedestrian index of the environment (PIE), a detailed and fine-grained measure developed previously by the authors (Singleton et al., 2014b).
- *Pedestrian barriers*: Barriers or deterrents to walking such as steep slopes, higher traffic speeds and volumes, parking characteristics, and industrial land uses may affect the choice of destination.
- *Socioeconomic characteristics*: Traveler characteristics like income or age may moderate some of these effects.

4. Methods and data

Our framework for pedestrian destination choice is shown in Fig. 2. It consists of three processes:

1. Aggregating PAZs used in the trip generation step to slightly larger geographic zones called superPAZs (0.25 mi (0.40 km) on a side), which are grids of 5 × 5 PAZs.
2. Applying an estimated destination choice model.
3. Allocating trips from superPAZs to PAZs within them.

Here, we focus on pedestrian destination choice model estimates for step 2. We also summarize one relatively simple and practical approach to implementing step 3. Methodological options for the third step include using a gravity-type model to allocate trips, applying the superPAZ-based destination choice model estimated in step 2 at this finer scale, or estimating a new PAZ-allocation model. While the most theoretically-rigorous approach may be to estimate a PAZ-allocation model or an omnibus destination choice model with PAZs nested within superPAZs, we leave this task for future work. Instead, we decided to re-apply the superPAZ-level model from step 2 when allocating trips to PAZs in step 3.

To examine destination choice behavior among pedestrians, we estimated multinomial logit destination choice models 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:

$$P_{j,i} = \frac{e^{V_{j,i}}}{\sum_{k \in K} e^{V_{k,i}}} \tag{1}$$

Destination alternatives consisted of superPAZs. We chose to analyze pedestrian destination choice using superPAZs instead of individual PAZs for a number of reasons. Practically, this geographic unit was chosen over PAZs to lessen computation times for data processing, model estimation, and application in a regional context. In addition, at only 0.25 mi (0.40 km) per side, superPAZs still capture a substantial amount of variation in the pedestrian environment and reduce the potential for completely-intrazonal walk trips. Furthermore, superPAZs are roughly the size of the smallest TAZs, even in the densest parts of downtown Portland. Overall, superPAZs are still a substantial improvement over TAZs for pedestrian behavior analysis. Of course, superPAZs (and PAZs) may obscure variation within them or introduce difficulties when dealing with large land uses that span multiple zones (e.g., parks, shopping centers, campuses). SuperPAZs also reduce the accuracy of trip distances, since trips are assumed to take place between SuperPAZ centroids rather than PAZ centroids. While this assumption introduces some error into the destination choice modeling process, the error (as a percentage of trip length) is smaller for longer-distance trips and is not biased in any particular direction. These tradeoffs are discussed elsewhere (Clifton et al., 2016; Singleton et al., 2014a).

We considered several choice set generation methods, including simple random sampling, stratified importance sampling (Ben-Akiva and Lerman, 1985), and strategic sampling (Lemp and Kockelman, 2012). For this study, we generated choice sets consisting of a simple random sample of ten superPAZs (including the chosen zone) with centroids located within a 3.0 mi (4.8 km) network distance of the production zone. More than 99% of observed walk trips in our estimation dataset were less than 3.0 mi in length. Future work will examine larger choice sets and strategic sampling methods to reduce potential bias in our parameter estimates.

To estimate the pedestrian destination choice models, we used 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 (not including access and egress trips). The OHAS data contained 4511 walk trips (8%, unweighted); this quantity underestimates the total amount of walking by excluding access/egress trips such as those associated with using public transportation. Trip origins and destinations were located using addresses and assigned to PAZs and superPAZs. Of walk trips, 44% were TAZ-intrazonal. By comparison, only 25% were superPAZ-intrazonal and 9% PAZ-intrazonal, highlighting another advantage of using smaller spatial units to represent walking. Walk trips and destination choice models were segmented by six trip purposes: home-based work (HBW), shopping (HBS), recreation (HBR), and other (HBO); and non-home-based work (NHBW) and non-work (NHBNW). Home-based school trips were not modeled because of the complexities of school assignment policies.

Destination choice utility equations were specified using measures of impedance Imp, a log-sum of size terms s, pedestrian trip supports p and barriers b, and traveler characteristics c as shown in the following utility equation and detailed below:

$$V_{j,i} = \sum_{c \in C} \beta_{Imp,c} Imp_{ij} TC_c + \beta_{size} \ln \left[\sum_{s \in S} (e^{\beta_s} Size_{s,j}) \right] + \sum_{p \in P} (\beta_p Support_{p,j}) + \sum_{b \in B} (\beta_b Barrier_{b,j}) \tag{2}$$

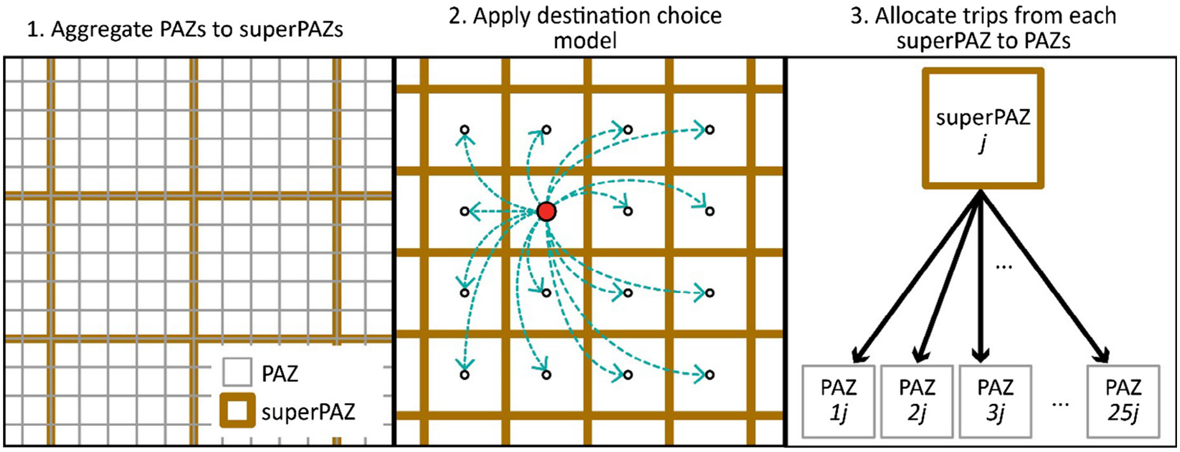

Fig. 2. Framework for pedestrian destination choice.

- *Impedance* (Imp_{ij}): As a measure of impedance, we calculated the shortest path distance (in miles) between the centroid of zones *i* and *j* along a network that included the complete street network (excluding limited-access highways) and major off-street paths. Street and path network layers came from the 2011 version of the Regional Land Information System, or RLIS (Metro, 2011).
- *Size/attractiveness* ($Size_{s,j}$): Size terms included zonal employment by type and (for some purposes) the number of households. Employment categories were retail trade, service, finance/insurance/real estate, government, agriculture/forestry/mining, construction, manufacturing, transportation/communications/utilities, and wholesale trade. Employment data came from the 2009 Quarterly Census of Employment and Wages (QCEW) database (BLS, 2009). Consistent with destination choice practices, size terms were summed and logged, yielding a nonlinear-in-parameters specification. Internal size parameters were exponentiated to prevent negative values within the natural log. Size terms were scaled such that the coefficient for service employment (the largest category) equaled 1 ($\beta_{EmpService} = 0 \rightarrow e^0 = 1$).
- *Pedestrian supports* ($Support_{p,j}$): We included pedestrian environment measures to represent supportive conditions in the destination zone. The primary measure of a supportive pedestrian environment was the pedestrian index of the environment, or PIE. The PIE—a 20–100 score calibrated to walking behavior using binary logit regressions on walk mode choice—captured the effects of activity density, block density, sidewalk density, transit access, neighborhood-oriented businesses, and other factors. High scores were in the densest parts of downtown Portland, while low scores were in rural, forested, or otherwise undeveloped parts of the region (Clifton et al., 2013; Singleton et al., 2014b). The PIE was a significant predictor of walk mode choice (Clifton et al., 2016). Pedestrian support variables also included the presence of parks (obtained through RLIS) for some purposes.
- *Pedestrian barriers* ($Barrier_{b,j}$): Barriers to pedestrian travel measured for each destination zone included the mean slope, the presence of freeways, and the proportion of industrial-type employment (agriculture/forestry/mining, construction, manufacturing, transportation/communications/utilities, and wholesale trade) as a proxy for industrial land uses. Slope was calculated using the 1/3 arc-second bare earth digital elevation models from the National Elevation Dataset (USGS, 2014). Freeway data came from RLIS; land uses and employment were also from QCEW data.
- *Traveler characteristics* (TC_c): We also examined the interaction of impedance with certain traveler characteristics from OHAS data, including household income, auto ownership, and the presence of children. Results for models using impedance interacted with household income are not shown as differences were either not significant or less significant than with auto ownership and children.

For the size variables and the pedestrian barriers and supports, we aggregated data captured at the PAZ level to the superPAZ. Depending on the data type, PAZ-level values were summed (employment by type, households), averaged (PIE, slope), or otherwise calculated (parks, freeways) across all PAZs within a superPAZs, as appropriate.

Table 1 summarizes descriptive statistics for the variables used in pedestrian destination choice modeling. Descriptive statistics for destination-specific variables (all except for traveler characteristics) include only those zones that were chosen.

Models were estimated using Python Biogeme Version 2.3 (Bierlaire, 2003). Model estimation proceeded sequentially, adding all of the variables in each of type and removing or grouping insignificant ($p > 0.10$) parameters (among impedance and size variables only) for parsimony before considering the next variable type.

As previously mentioned, we did not estimate a new PAZ-level model for step 3 (allocating trips from superPAZs to PAZs). Instead, we borrowed the step 2 model and used the model coefficients (with the exception of distance) when applying the PAZ-level destination choice model, contingent on the prior choice of superPAZ. Choice sets consisted of all 25 PAZs within a particular superPAZ; PAZ-level data were used instead of superPAZ-level data.

Table 1
Descriptive statistics for pedestrian destination choice model variables.

		HBW	HBS	HBR	HBO	NHBW	NHBNW
Sample size		305	405	643	1108	732	705
Impedance							
Distance (miles)	Mean (SD)	0.75 (0.79)	0.57 (0.49)	0.53 (0.51)	0.51 (0.49)	0.38 (0.39)	0.41 (0.46)
Size/attractiveness							
Retail jobs (#)	Mean (SD)	223 (537)	299 (431)	62 (202)	106 (259)	845 (1053)	419 (760)
Service jobs (#)	Mean (SD)	398 (971)	216 (590)	102 (331)	136 (441)	1689 (1863)	611 (1313)
Finance jobs (#)	Mean (SD)	151 (479)	83 (336)	24 (99)	43 (211)	827 (1147)	200 (536)
Government jobs (#)	Mean (SD)	207 (668)	76 (227)	28 (129)	55 (241)	904 (1484)	308 (799)
All other jobs (#)	Mean (SD)	66 (126)	31 (71)	30 (85)	35 (95)	165 (183)	75 (143)
Households (#)	Mean (SD)	206 (208)	324 (442)	174 (160)	197 (197)	325 (324)	283 (337)
Pedestrian supports							
Park (yes)	# (%)	182 (60%)	257 (63%)	480 (75%)	677 (61%)	555 (76%)	458 (65%)
PIE, mean	Mean (SD)	51 (27)	56 (26)	44 (22)	46 (26)	75 (25)	58 (28)
Pedestrian barriers							
Slope (degrees), mean	Mean (SD)	1.63 (1.45)	1.27 (0.90)	1.83 (1.75)	1.37 (0.88)	1.38 (0.84)	1.44 (1.13)
Freeway (yes)	# (%)	33 (11%)	19 (5%)	33 (5%)	61 (6%)	106 (14%)	99 (14%)
Industrial jobs (prop.)	Mean (SD)	0.10 (0.16)	0.06 (0.1)	0.19 (0.26)	0.14 (0.21)	0.07 (0.13)	0.09 (0.16)
Traveler characteristics							
Auto ownership (yes)	# (%)	237 (78%)	301 (74%)	589 (92%)	1019 (92%)	689 (94%)	592 (84%)
Children (yes)	# (%)	91 (30%)	117 (29%)	279 (43%)	628 (57%)	222 (30%)	292 (41%)

5. Results

Model estimation results for the six purpose-specific destination choice models are presented in Table 2. McFadden's adjusted pseudo-R^2 values ranged from 0.416 for home-based recreation to 0.680 for home-based shopping purposes. Results were consistent with intuition and previous studies of pedestrian behavior.

Distance was a significant deterrent when choosing a destination: a 1.0 mi (1.6 km) increase in network distance to a particular destination yielded about an 80% decrease ($e^{B_{imp}} - 1$) in the odds of choosing that destination. The average sensitivity to that 1.0 mi increase in distance ranged from a 62% decrease in odds for home-based work walk trips (for zero-vehicle households) to a 90% decrease in odds for home-based shopping walk trips (for households with children). Distance was a stronger deterrent to walking for home-based shopping and other trips, while people were willing to walk further from home to get to work than for other purposes. For home-based other and non-home-based walk trips, there were no significant interactions between distance and the traveler characteristics of auto ownership and children. There was a significant distance–auto ownership interaction for home-based work walk trips: people in zero-car households were less sensitive to distance than people from households that owned at least one car. There were also significant distance–children interactions for home-based shopping and recreation walk trips: people in households with children were more sensitive to distance.

Measures of the size of destinations were significant positive predictors of walk trip destination choice: doubling the number of jobs and households in a zone for several purposes (HBW, HBO, NHBW, NHBNW) yielded a 28–42% increase ($2^{B_{size}} - 1$) in the odds of choosing that destination zone (elasticities were 0.36–0.51). Destination choice for home-based recreational walk trips was not strongly influenced by the destination zone size (elasticity was 0.05). However, the destination choice odds for home-based shopping walk trips was almost unit elastic with respect to employment (0.91); doubling the number of jobs increased the odds by 88%. The destination choice models also estimated the relative attractiveness of different types of employment or households for different purposes. For example, the number of retail jobs were overwhelmingly the dominant attractive force for home-based shopping walk trips: one additional retail job was equivalent to about 230 (e^{B_s}) additional jobs of other types.

Supportive pedestrian environments in destination zones also attracted walk trips: a ten-point increase in the PIE score of a particular destination for non-home-based purposes yielded about a 16–18% increase ($e^{10 \cdot B_p} - 1$) in the odds of choosing that destination. The average sensitivity to a ten-point increase in PIE was highest for home-based work (a 34% increase in odds) and home-based other (a 28% increase in odds) walk trips. PIE was not a significant predictor of pedestrian destination choice for home-based shopping or recreation purposes. However, for home-based recreational walk trips, the presence of a park increased the odds of choosing that destination zone by 58%.

On the other hand, barriers to pedestrian travel deterred walking to some destinations. The mean slope (in degrees) in a destination zone was associated with a decreased odds of choosing that zone for several walk trip purposes (HBS, HBO, NHBW). In addition, the percentage of industrial-type jobs was negatively associated with pedestrian destination choice, significantly for four walk trip purposes (HBW, HBS, HBO, NHBW). The presence of a freeway was a significant deterrent to home-based shopping walk trip destination choice.

Table 2
Results of pedestrian destination choice models.

	Home-based work (HBW)			Home-based shopping (HBS)			Home-based recreation (HBR)			Home-based other (HBO)			Non-home-based work (NHBW)			Non-home-based non-work (NHBNW)		
Variable	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*
Distance (miles)	–	–	–	–	–	–	–	–	–	−1.94	0.062	0.00	−1.42	0.067	0.00	−1.45	0.054	0.00
× Auto (yes)	−1.35	0.124	0.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
× Auto (no)	−0.96	0.182	0.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
× Child (yes)	–	–	–	−2.26	0.174	0.00	−1.75	0.074	0.00	–	–	–	–	–	–	–	–	–
× Child (no)	–	–	–	−1.52	0.140	0.00	−1.51	0.063	0.00	–	–	–	–	–	–	–	–	–
Size terms (ln)	0.51	0.074	0.00	0.91	0.089	0.00	0.05	0.019	0.01	0.40	0.034	0.00	0.36	0.054	0.00	0.39	0.055	0.00
Retail jobs (#)	2.0	0.85	0.02	5.5	0.71	0.00	6.5	1.36	0.00	3.8	0.57	0.00	5.5	0.66	0.00	5.5	1.05	0.00
Government jobs (#)	2.0	0.85	0.02	0.0	–	–	17.1	5.65	0.00	3.8	0.57	0.00	0.0	–	–	3.4	1.23	0.01
Finance jobs (#)	2.0	0.85	0.02	0.0	–	–	0.0	–	–	0.0	–	–	2.5	1.12	0.03	0.0	–	–
All other jobs (#)	0.0	–	–	0.0	–	–	0.0	–	–	0.0	–	–	0.0	–	–	0.0	–	–
Households (#)	–	–	–	–	–	–	−3.2	1.34	0.02	−2.0	0.87	0.02	–	–	–	0.8	1.26	0.52
Park (yes)	–	–	–	–	–	–	0.46	0.127	0.00	0.12	0.094	0.22	–	–	–	–	–	–
PIE, mean	0.030	0.010	0.00	−0.014	0.012	0.24	0.011	0.007	0.11	0.025	0.007	0.00	0.015	0.007	0.02	0.017	0.006	0.01
Slope (degrees), mean	−0.12	0.079	0.15	−0.20	0.100	0.05	−0.05	0.049	0.28	−0.43	0.062	0.00	−0.16	0.056	0.01	−0.06	0.051	0.24
Freeway (yes)	−0.30	0.260	0.25	−1.02	0.350	0.00	−0.17	0.213	0.43	0.10	0.191	0.60	−0.14	0.166	0.40	0.26	0.159	0.10
Industrial jobs (prop.)	−0.99	0.480	0.04	−1.74	0.609	0.00	−0.09	0.205	0.66	−0.40	0.224	0.08	−1.65	0.436	0.00	−0.24	0.350	0.50
Sample size (# walk trips)	305			405			643			1108			732			705		
Initial log-likelihood	−694			−925			−1459			−2511			−1648			−1590		
Final log-likelihood	−371			−288			−841			−1181			−675			−716		
McFadden's adjusted pseudo-R^2	0.453			0.680			0.416			0.526			0.585			0.544		

The model estimation results also suggested some important tradeoffs between attributes of alternatives in the pedestrian destination choice problem, as shown in Fig. 3. Comparing modeled sensitivities to size versus impedance, people were willing to walk longer distances to reach destinations with more jobs/households. For example, people were willing to walk 0.26–0.41 mi (0.41–0.67 km) further to reach destinations with twice as many jobs for home-based work and shopping purposes. People were also willing to walk longer distances to reach destinations with more attractive pedestrian environments: 0.11–0.31 mi (0.17–0.50 km) further to destinations ten-points higher on the PIE scale. Furthermore, improving the pedestrian environment of a destination was as attractive as increasing the number of jobs/households located there. Increasing a destination's PIE score by ten points was equivalent to increasing the number of jobs/households there by 52–85%.

As additional assessments of model goodness-of-fit, we applied the pedestrian destination choice models to the OHAS walk trip data used for estimation. Our results indicated relatively good performance. For all trip purposes except home-based recreation, the actually-selected destination superPAZ had the highest modeled probability in more than half the cases. For the home-based shopping purpose, the correct destination had the highest probability for 75% of walk trips. Furthermore, for most purposes, the actually-selected destination had a high probability of selection from the destination choice models. The mean modeled probability of the correct destination superPAZ was typically in the 0.41–0.50 range, with a low of 0.33 (home-based recreation) and a high of 0.62 (home-based shopping).

6. Discussion

This paper is one of the first to model the destination choice dimension of pedestrian travel behavior within a regional context. Its primary unique contributions are: a focus exclusively on pedestrian travel, analysis at a pedestrian scale, and inclusion of pedestrian-relevant variables. More specifically, our analysis relies on a uniform zonal system—264 ft- (80 m-) square gridded PAZs nested within 0.25 mi- (400 m-) square superPAZs; sizes commensurate with the spatial extent of walk trips—and includes traveler characteristics, pedestrian environment variables, and common destination choice variables (impedance and size).

Results suggest important behavioral influences related to walking. Distance is the major influence on pedestrian destination choice. Sensitivity to distance varied across trip purposes and was affected by traveler characteristics such as auto ownership and children in the household. The size or attractiveness of destinations is also important for walking behavior; people were willing to walk further to reach zones with more jobs, especially retail jobs, particularly for home-based shopping trips. The built environment also matters, as more attractive pedestrian environments supported walking to those areas while terrain and industry were deterrents. While our results cannot directly address the causal effects of pedestrian supports and barriers on walking behavior—given the cross-sectional nature of our data—these findings are consistent with our hypotheses. Furthermore, this research provides additional evidence towards a growing literature on significant associations between the built environment and walking.

Our results also highlight the importance of a few potential land use and transportation policy-levers that may act to encourage walking. As Fig. 3 indicates, increasing the number of activity opportunities (as measured by employment) in a regional center or neighborhood commercial corridor could encourage people to walk from farther away to reach that area. While such a change may also increase travel by other modes, increasing the activity density of an area would likely increase the pedestrian mode share of trips (Clifton et al., 2013, 2016), assuming a sufficiently-large adjacent residential population. The urban design of such areas is also important; walking to and within suburban strip developments could be made more attractive by installing sidewalks, connecting street grids, and encouraging neighborhood-oriented businesses, all key components of our PIE measure. Although we cannot make claims of causality in our findings, as mentioned above, these built environment attributes are associated with walking behaviors in our models and consistent with the literature in this area.

This work has many potential applications for transportation planning. The most direct planning application for our pedestrian destination choice models is through the modification of regional travel demand forecasting tools to better represent walking activity. These products could also function as a standalone pedestrian planning tool, separate from a parent travel demand model. Such tools have a wide range of applications, not limited to simply identifying locations with high pedestrian activity or prioritizing investments in pedestrian infrastructure based on their potential to increase walking levels. For instance, improved models of walking demand can also be used to generate more accurate risk exposure estimates for transportation safety analyses or as inputs to health impact assessment tools; although, such applications are beyond the scope of this paper.

Our research also has many potential extensions. Since we have developed models to predict pedestrian trip generation (Clifton et al., 2013, 2016) and now destination choices, the next logical step is to extend this effort into predicting potential routes or paths. The PAZ spatial unit is used in both stages and may accelerate a route-level analysis. Raster paths could be analyzed to highlight potential routes traversed between modeled origins and destinations in order to estimate an overall view of pedestrian activity. A valuable alternative approach—given sufficient data on walking routes—would be to estimate a pedestrian route choice model that incorporates path-based characteristics of the street-level built environment, and then use this model to generate more realistic measures of pedestrian impedance (e.g., using route choice log-sums or most desirable paths, instead of shortest-path distance) and route-based pedestrian supports and barriers for use in our destination choice model. An additional extension could then use log-sums from the destination choice model to feedback as an input variable in the walk mode split model, tying the pedestrian modeling framework together.

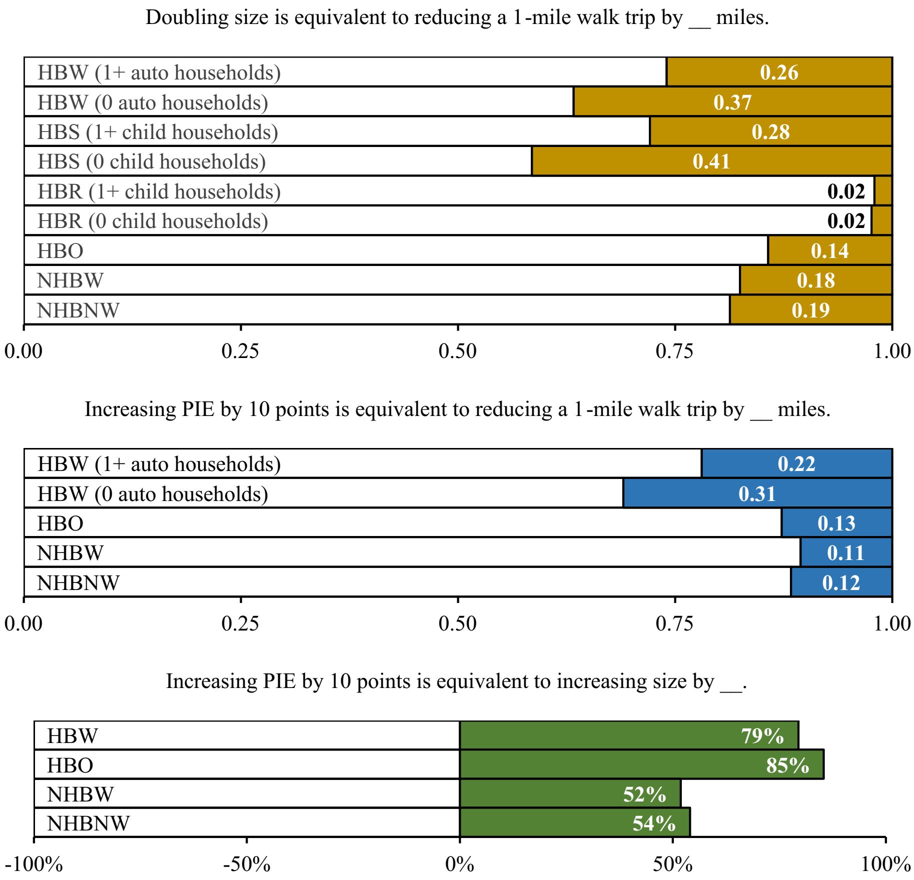

Fig. 3. Relative sensitivities of pedestrian destination choice attributes.

In this paper, the destination choice dimension of pedestrian behavior was chosen for study because the effort is one component of a larger pedestrian forecasting model. The model operates within a modification of the common four-step travel demand modeling process (trip generation, trip distribution, mode choice, trip assignment). In the pedestrian forecasting model, trips are first generated, then a mode (pedestrian, vehicle) is chosen, and finally the trips are distributed. As such, the choice of destination for an activity is considered sequentially after the trip is generated and the walk mode is chosen. In reality, destination choices are probably considered along with choices of mode, time of day, activity, and whether to travel at all. This larger issue affects both trip- and activity-based travel forecasting models and has been questioned by many authors (e.g., Pas, 1985). Future work could address this concern, examining the extent to which people choose destinations and modes sequentially (and in which order) versus simultaneously. Particularly, there is also a need for more qualitative research on pedestrian travel behavior, including how destination- and route-level characteristics affect choices for pedestrians. This work could build upon the large body of research on mode choice and motivations for walking and could help inform quantitative route-level analyses.

In the future, our work can be refined in a number of ways to yield a greater understanding of influences on pedestrian travel behavior, particularly around destination choice. First, because of the regional scope of this application of the destination choice model, we were unable to obtain micro-level data for the entire study area on pedestrian barriers like number of lanes, traffic speeds and volumes, and information on intersections like treatments and crossing conditions. These are all identified as important factors for pedestrian suitability analysis (Dowling et al., 2008; Lagerwey et al., 2015). Such smaller-scale information on the street-level built environment may be recorded by local jurisdictions, but it is rarely shared or standardized across an entire region. This limitation may be addressed in the future as this type of information becomes available. In the meantime, micro-scale data on pedestrian barriers could be included in a fined-grained pedestrian destination choice model by focusing on, for instance, walk trips fully within the City of Portland.

Second, data limitations also prevented us from investigating the influence of attitudes and perceptions of the built environment on pedestrian destination choice. Our travel survey data did not ask respondents about their attitudes towards the safety of particular street crossings or perceptions of pleasant walking areas. Evidence has shown perceptions to be stronger predictors of non-motorized travel behavior than objective measures of the built environment (e.g., Ma et al., 2014). Theory suggests that attitudes and perceptions of the safety, security, convenience, and enjoyment of different travel options should have a strong impact on walking behavior (Schneider, 2013; Singleton, 2013). Future studies could consider collecting and analyzing psychosocial data; although, such qualitative data are more difficult to predict and apply for forecasting purposes.

Third, there may also be room to incorporate agglomeration and competition effects into the modeling effort. Destinations located in close proximity to other complementary types of destinations (e.g., in a shopping district) may yield trip-chaining efficiencies that increase their attractiveness. On the other hand, a concentration of similar destinations (e.g., multiple food outlets) might provide option value or may dilute market shares (Bernardin et al., 2009).

Fourth, it would be useful to consider additional sources and forms of taste heterogeneity due to traveler characteristics. Our only sources of heterogeneity were significant interactions of the impedance variable and auto ownership and the presence of children for some trip purposes (household income was less or not significant). Future work should examine potential variations in sensitivity to size and built environment variables, including pedestrian barriers and supports. It may also be useful to examine random taste heterogeneity, such as through the use of mixed logit models.

Fifth, more sophisticated destination choice modeling may also yield modest improvements. Scholars have raised issues associated with model performance due to choice set generation methods, the number of alternatives to sample, and model structure (Bhat et al., 1998; Nerella and Bhat, 2004; Pagliara and Timmermans, 2009). In model development, we chose a relatively basic MNL structure and used a simple random sample of ten zones for our choice set. Some authors have suggested sampling a larger number or proportion of alternatives (Nerella and Bhat, 2004). However, other destination choice work using the same dataset found that estimation results did not change substantially when using choice sets of 10 or 25 (Singleton and Wang, 2014). Furthermore, this lack of coefficient variation as a function of the choice set size has been found in other studies (de Palma et al., 2007). Therefore, we feel confident our results may be relatively robust to increases in destination choice sizes. Future estimations can incorporate more sophisticated sampling approaches, such as increasing the number of sampled zonal alternatives and implementing a probability feedback loop into the sampling method (e.g. strategic importance sampling (Lemp and Kockelman, 2012)). Additional work is also needed to investigate how the choice of superPAZ size impacts the accuracy of the model-estimated trip distance coefficient. It may be possible to improve the precision of this distance coefficient, although this coefficient already has one of the smallest standard errors in the model. Subsequent efforts may also consider alternative methods to allocate trips from superPAZs to PAZs.

Despite these limitations, this modeling effort has advanced the understanding of pedestrian destination choice behaviors and tested their associations with a variety of built environment and travel characteristics. This is a reasonable first step, given the dearth of research on this topic, and one conducted with an eye towards improving practice. The increasing availability of spatially disaggregate travel behavior and built environment data have created opportunities to improve the representation of non-motorized modes in our predictive planning tools. More fundamental study of the travel behaviors of pedestrians and travelers' decision processes is needed to inform the development of these types of tools as many questions remain about the motivations and influences of pedestrian behaviors.

Acknowledgements

This work was conducted under a research project (Clifton et al., 2015) sponsored by the National Institute for Transportation and Communities (TREC), a program of the Transportation Research and Education Center (NITC) for Portland State University, which received funding from the US Department of Transportation and Metro. The comments from five referees improved this paper.

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