Multimodal Trip Generation Model to Assess Travel Impacts of Urban Developments in the District of Columbia

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The research effort described in this paper aims to develop a state-of-the-practice methodology for estimating urban trip generation from mixed-use developments. The District Department of Transportation's initiative focused on (*a*) developing and testing a data collection methodology, (*b*) collecting local data to complement the ITE's national data in trip rate estimation, and (*c*) developing a model–tool that incorporates contextual factors identified as affecting overall trip rate as well as trip rate by mode. The final model accurately predicts total person trips and mode choice. The full set of models achieves better statistical performance in relation to average model error and goodness of fit than either ITE rates alone or other existing research. The model includes sensitivity to local environment and on-site components. The model advances site-level trip generation research in two major ways: first, it calculates total person trips independent of mode choice; second, it calculates mode choice with sensitivity to the amount of parking provided on site—a major finding in the connection between parking provision and travel behavior at a local-site level. The methodology allows agencies to improve their assessment of expected trips from proposed buildings and therefore the level of impact a planned building may have on the transportation system.

The expected magnitude of environmental and travel impacts from proposed land use development hinges on trip generation rates used in the analysis of the site. Common practice is the use of the ITE *Trip Generation Manual,* 9th edition, as the key reference to derive appropriate estimates of vehicular traffic generation (*1*). ITE is an extensive and robust data source, with vehicle trip generation rates for hundreds of land uses for multiple periods (*2*). However, ITE's trip generation rates are primarily based on automobile-oriented single-use suburban developments and do not forecast multimodal travel by nonauto modes. This approach counts the number of vehicles from a development rather than the number of people, which generally means that the rates are poorly suited to assess impacts of mixed-use development sites in multimodal urban areas that can have considerable nonvehicle trip making. Considering trips by modes is particularly important for Washington, D.C., and similar cities where mixed-use developments with significant volume of nonauto traffic are common.

The latest ITE *Trip Generation Handbook,* 3rd edition, provides guidance on how to estimate vehicle trips in transit-oriented mixed-use urban development settings (*2*). But as a result of ITE's automobile focus, the application of ITE's trip rates to estimate vehicle trips generated by mixed-use development sites located in transit-rich, high-density cities with parking constraints likely leads to an overestimation of vehicular trips and parking demand and an underestimation of nonvehicular trips. This situation has several implications for cities:

- Inaccurate infrastructure investment decisions, such as overinvestment in vehicle capacity expansion and parking infrastructure and underinvestment in pedestrian, bicycle, and transit infrastructure;
- Overprediction of environmental impacts, including air quality and greenhouse gas emissions levels; and
- Fewer incentives to develop "smart" infill, mixed-use developments as developers do not receive credit for reduced automobile trip-making patterns.

Motivated by these issues, the District Department of Transportation (DOT) undertook a research effort in 2013 to develop an improved methodology for estimating urban trip generation from mixed-use developments in a dense urban environment that accounts for nonautomobile trips. This process included (*a*) developing and testing a data collection methodology, (*b*) collecting local data to complement the ITE's national data in trip rates estimation, and (*c*) developing a model–tool that incorporates contextual factors identified as affecting overall trip rate as well as trip rate by mode. This initiative was divided into three phases: Phase 1, initial data collection and observations; Phase 2, additional data collection and preliminary modeling; and Phase 3, refinement of final model and tool development.

TRIP GENERATION IN AN URBAN SETTING: EVIDENCE FROM THE LITERATURE

Increasingly, urban trip generation has been the focus of many studies that can be divided into two broad groups. The first group includes studies that analyzed the effects of urban context variables

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on trip generation or associated travel behavior, such as vehicle miles traveled (VMT). Many studies have examined links between built environment and demand for travel. The built environment generally refers to the D-variables: density, diversity, design, development scale, demographics, distance to transit, and destination accessibility. In one of the earlier studies, Cervero and Kockelman explored the effect of density, diversity, and design on household VMT and mode choice for non-commute trips and found that these D-variables have a negative impact on household VMT and positive impact on nonauto mode choice (*3*). Ewing and Cervero, after an extensive literature review, concluded that, in addition to producing shorter trips, built-environment criteria are likely to foster substitution between auto trips and nonauto trips (*4*). Zhang et al. (*5*) and Ewing et al. (*6*) also found a negative correlation between VMT and high-density, mixed-use developments. A number of studies found association between auto trips and transit proximity. For example, Clifton et al. found that proximity to transit plays a role in reducing vehicle trips (*7*), while Ewing and Cervero suggested that proximity to transit is likely to induce fewer vehicle trips and more walk and transit trips (*4*). In the same study, Ewing and Cervero found a strong relationship between VMT and destination accessibility.

Several studies have identified parking availability and pricing as important context variables. Cervero et al. found that most transit-oriented developments have more parking spaces than required (*8*). This finding was also supported by Tian et al. (*9*). An oversupply of parking spaces may lead to an increase in auto ownership and auto trips. Indeed, agencies in areas rich in transit-oriented developments, such as the District DOT (*10*) and King County, Washington (*11*), have recently developed models and web-based tools in an effort to provide more accurate estimation of parking needs for multifamily residential buildings. The data underlying the District DOT study indicate that most residential parking garages in the District are underutilized. A study by Frank et al. noted strong negative correlation between parking cost and VMT; that is, a noticeable increase in parking cost is likely to decrease VMT (*12*).

The second group of studies focused on estimation of trip generation. Specifically, these studies focused on offering alternatives to ITE trip generation rates that are more suitable for urban transit-oriented, mixed-use developments. Examples of such studies include these:

- URBEMIS 2007 (2007). Outputs include ITE-based vehicular trip reductions (*13*).
- EPA-MXD Traffic Generated by Mixed-Use Developments (2011): Outputs include ITE-based vehicular trip reductions, ITE-derived transit trips, ITE-derived walking trips, and internally captured trips (*14*).
- SANDAG MXD Trip Generation for Smart Growth (2010). This is an adaptation of the EPA-MXD model (*15*).
- *NCHRP Report 684* (2011). Outputs include ITE-based vehicular trip reductions (*16*).
- California *Smart Growth Trip Generation* (2014). Outputs include ITE-based vehicular trip reductions (*17*).
- *NCHRP Report 758* (2013). Outputs include ITE-based vehicular trip reductions (*18*).
- MXD+ (2013). This covers a refined methodology combining EPA-MXD and *NCHRP Report 684* (*19*).
- Portland State University models (2012). Outputs include ITE-based vehicular trip reductions and trips by mode (*7*).

A subset of the research on trip generation estimates has started to investigate the concept of person trip generation, especially in an urban context. An early finding of this research was that the overall person trips were much higher than expected via ITE (even with a vehicle occupancy factor) alone. Existing research has observed this result from different angles, such as the finding that common trip generation methodologies overestimate vehicle trips while underestimating person trips (*20*) and direct discussions of person trips for smart-growth infill projects (*21*).

The literature has suggested that the benefits of using ITE as a basis of trip generation include a large established database of rates by land use, widespread industry acceptance, and relative ease of use. One potential drawback includes sacrificing local context for the breadth of data at the national level. ITE itself has recognized the need to move toward person-based trip generation, especially in urban areas, and created an urban trip generation panel to guide efforts to develop appropriate urban trip generation products (*22*).

PHASE 1. LOCAL DATA COLLECTION AND OBSERVATIONS

The first step in the District DOT's urban trip generation research was to develop and test a data collection methodology. For Phase 1 data collection, the research team compiled an initial list of 185 sites–buildings in the District. Next, each site was assessed against the following key criteria to be considered suitable for data collection:

- Size. Larger buildings, typically 75 or more residential units.
- Use. Predominantly residential with a retail component. Retail includes a mix of types of stores that serve both local (i.e., neighborhood retail) and nonlocal customers (i.e., destination retail). Examples include convenience stores, grocery stores, dry cleaners, and specialty foods stores.
- Location. Throughout the District. However, most sites that met the size and mixed-use criteria were located in areas with rich public transportation options, bicycle facilities, and grid street layout.
- Occupancy. Sites at or near full occupancy for both residential and retail components.
- Parking. Ideally, separate parking for retail and residential uses.

From the initial list, 16 sites were chosen for Phase 1 data collection. Data were collected at those sites in November and December 2013 and February 2014 in 15-min intervals between 7:00 and 10:00 a.m. and 4:00 and 7:00 p.m., and collection involved counting the number of vehicles and persons entering–exiting each building site through all garages and doorways. A short intercept survey was undertaken whereby a convenience sample of individuals was asked about their access–egress modes to–from the building site. These data were summarized, and lessons from that data collection served as a basis for refining a methodology for collection of multimodal trip generation data from urban mixed-use developments (*23*).

After the successful Phase 1 data collection, data were collected at an additional 46 sites in Phase 2, between April and June 2015, for a total of 62 sites. Table 1 summarizes the land use types and key site attributes. Most of these 62 sites were then used as the basis for the preliminary modeling developed during Phase 2, with some sites not meeting the criteria listed earlier being eliminated.

TABLE 1 Sites by Land Use and Characteristics

			Average (range)			
Land Use	Retail Type	Site Count	Dwelling Units	On-Site Parking (spaces)	Retail Space (kilo square feet)	Residential Occupancy
Residential + retail	Neighborhood	39				
	Destination	9				
Residential only	na	8	218 (40–536)	203 (0–783)	20.7 (1.1–110.4)	93.8% (78.9%–100%)
Office + retail	Neighborhood	3				
Hotel + retail	Neighborhood	3				
	Destination	0				

NOTE: na = not applicable.

PHASE 2. DISTRICT DOT PRELIMINARY TRIP GENERATION MODELS

Phase 2 of the District DOT's work included the development of two trip generation models to attempt to create a trip generation methodology that worked best for the District. These two models are the multimodal accessibility (MMA) method and the District DOT MXD+ method.

The MMA method examined relationships between person trip rates, vehicle trip rates, mode shares, and a number of environmental variables, including these:

- Multimodal accessibility scores describing site-specific access to jobs and retail opportunities by all modes,
- Neighborhood auto ownership levels and population density, and
- On-site parking supply.

The analysis could not identify a significant relationship between any of these variables and trip rates or mode shares. As a result, the final MMA methodology was a series of static trip rates that are a function of the magnitude of land use development (e.g., dwelling units or thousands of square feet of commercial development).

While this methodology is an improvement over ITE trip generation rates because it is based on data collected in the District and generates vehicle and person trip estimates by mode, the MMA method does not provide comprehensive context sensitivity.

The MXD+ method, initially developed for the U.S. EPA, accounts for the degree to which mixed-use sites internally capture travel demand and the extent to which smart-growth site design and context result in walking, biking, and transit use on a national scale. The EPA MXD+ method was calibrated for District conditions on the basis of data collected and local household survey records, and the model structure was not altered in Phase 2. The resulting District DOT MXD+ method estimates auto, transit, pedestrian, and bicycle modes.

The relative results for the initial District DOT MXD+ method illustrated a need for further improvements. The MXD+ research was focused on auto trips that were based on large sites not confined to urban areas. The calibration of this model to fit District DOT's high-density urban sites resulted in an average model error that was much greater for walk, bike, and transit trips than for auto trips in both the morning and evening, and the discrepancy in validation between the auto mode and nonauto modes represented an initial step at new insight for a finer-grained level of multimodal analysis. The results of Phase 2 were promising, however, and demonstrated that an urban trip generation method calibrated to District conditions could be achieved.

PHASE 3. DISTRICT DOT URBAN TRIP GENERATION MODEL

Phase 3 started with the findings from the MXD+ Phase 2 efforts and conducted further statistical analysis to create a District DOT Urban Trip Generation Model (i.e., District DOT MXD+). The ultimate goal of District DOT MXD+ was to predict person trips per development site per mode. Three areas for enhancement were identified: (*a*) improving the model's ability to predict person trips, (*b*) testing on-site parking supply as an additional variable influencing mode choice, and (*c*) enhancing the transit accessibility measure to distinguish between good transit accessibility, which exists throughout most of the District, and great transit accessibility. Focusing on the residential-over-retail mixed-use sites resulted in 55 sites for analysis.

A set of statistical models was developed to predict (*a*) total person trips and (*b*) traveler mode choice. The original data were structured at the site level and contained variables for total trips and mode share by each of five modes: auto driver, auto passenger, transit, walk, and bike. Variables related to density, diversity, and land use were collected from the Metropolitan Washington Council of Governments, the Smart Location Database from the EPA, the ParkRight DC calculator, the ITE *Trip Generation Manual,* DC Geographic Information Systems Open Data, and the consultant team.

These variables were intended to be a cross section of the built environment within the District that could explain multimodal travel behavior. The majority of the variables were at the site-level scale, but a number of "neighborhood scale" (as defined by the D.C. Office of Planning) variables were tested. Both statistical models were estimated in the statistical package R, an open-source integrated suite of software facilities for data manipulation and calculation (*24*). More than 50 variables were considered and tested as part of the statistical analyses described below. Variables considered included those focused on density, diversity, auto ownership, and parking, along with other variables found to be significant in published literature. Through a hierarchical process of testing variables on the basis of multicollinearity and fit, the following models were created.

Person Trip Model

Phase 3 sought to improve the model's ability to predict person trips and resulted in a morning peak hour and evening peak hour model.

Concept and Methodology

The person trip modeling used the original data set at the site level and was fitted as a linear regression model. The dependent variable was the observed person trips from the original District DOT data. Independent variables included the D-variables identified previously. In addition, data from the ITE *Trip Generation Manual*, 9th edition, were used to obtain variables for person trips calculated by ITE's trip generation linear-fit equations on the basis of each site's respective land use code.

The linear regression was estimated by forming subsets of variables on the basis of an established hierarchy among variables that exhibited the least multicollinearity when tested together. This step was an automated process in the R software, which conducted the model-building process by successively adding or removing variables solely on the basis of t-statistics of their estimated coefficients.

The output of this automated process was a final model that represents a subset of independent variables that best fits the linear regression and provides a high-level understanding of how the independent variables work individually and in conjunction with each other. Revisions were made to the output model on the basis of testing for significance by p-value, intuitiveness for the magnitude and direction of the coefficients, and comparison with other findings in published literature.

Results

The variables resulting in the strongest-fitting model were the same for both the morning and the evening models. Table 2 lists the variables, units, and R software outputs for each model.

The results of the morning and evening models showed that the ITE vehicle trips that used the fitted equations were highly significant, with a positive coefficient against the dependent-variable-observed person trips. In the results, the intersection density variable for auto-oriented intersections per square mile was significant in the morning model but not the evening model. "Auto-oriented intersections," a variable calculated in the EPA Smart Location Database at the census block group, are defined as "intersections where automobiles are allowed but pedestrians are restricted, intersections of arterial streets signed as 55 mph or higher, intersections of one-way streets signed as 40 mph or higher, or intersections of arterial streets of four or more lanes of travel in a single direction." On the basis of intuitiveness, the threshold of significance was lifted to support the variables included in the evening model, but this finding indicates that the situation may be more nuanced and that the type of intersection density influences travel behavior.

These results indicate that the ITE *Trip Generation Manual* is a good basis for person trip generation, albeit limited and not overly explanatory. Planning theory has posited that person trip generation may be influenced by the same built environment D-factors as mode choice, but empirical research has been limited. These results indicate that those factors may be important, as noted by the inclusion of the design variable of intersection density. Further research is warranted. They also indicate that an adjustment to ITE rates with respect to the density of auto-oriented intersections is appropriate for an urban setting such as Washington, D.C. This model performs well for this data set but does not contain many degrees of freedom or sensitivity and as such should be considered preliminary and an opportunity for further research.

Mode Choice Model

The following sections explore the methodology of two mode choice models, one for the morning peak and one for the evening peak, and the results of the model estimations.

Concept and Methodology

A set of multinomial logistic regression models, or logit models, was developed to predict mode choice given various density and land use attributes for each site, as well as availability of transportation infrastructure. Multinomial logistic regression predicts the probabilities of different possible outcomes of a categorically distributed dependent variable given a set of independent variables that are either real valued, binary, or categorical (*25*). The logit model allows for more than two categories of the dependent or outcome variable, which is mode choice in this case. The logit model uses maximum likelihood estimation to evaluate the probability of categorical membership.

The logit model estimates probabilities among alternatives by using utility functions, which are meant to express the level of satisfaction

TABLE 2 Summary of Person Trip Model

Variable	Source	Estimate	SE	p-Value	Significance
a.m. Peak Hour ($R^2 = 0.8643$)					
ITE V trips (residential)	ITE	2.2279	0.2656	3.12 E–11	***
ITE V trips (commercial)	ITE	1.7033	0.4496	.000395	***
Auto-oriented int. density	EPA SLD	−6.8232	3.6373	.066282	*
p.m. Peak Hour ($R^2 = 0.8934$)					
ITE V trips (residential)	ITE	1.4978	0.2763	1.56 E–06	***
ITE V trips (commercial)	ITE	1.4264	0.155	1.67 E–12	***
Auto-oriented int. density	EPA SLD	−5.2903	4.6624	.262	

NOTE: int. = intersection; SE = standard error; SLD = Smart Location Database; V = vehicle.
*p-value < .1; **p-value ≤ .05; ***p-value ≤ .01.

or dissatisfaction with a given mode (*26*). Once the utility function is calculated for each mode, the probability that a given mode will be chosen can be calculated. This type of model is appropriate for mode choice, as the utility for each mode considers the attributes or features of each mode separately during the decision-making process. The expected maximum utility is the log sum of all the utility values. Probabilities depend on the differences in utilities, not actual values.

Independent variables in a logit model are either generic, meaning that they have the same value for all alternatives and will receive a different coefficient for each alternative, or alternative specific, meaning that each alternative has a different value for the variable and the variable will receive a single coefficient for all alternatives. In the present mode choice model, all variables are generic.

To estimate the logit model at the site level, data were restructured to the trip level and resulted in one observation for each choice situation (e.g., trip) per site. The five mode choice alternatives were these: auto passenger, transit, bike, walk, and the mode choice auto driver being the fixed reference-level alternative.

Models were estimated by analyzing a correlation matrix between every pair of independent variables to test for multicollinearity. Variables were then given a hierarchical priority on the basis of the correlation matrix and previous research. The independent variables, in order of priority on the basis of the literature review, started with those related to density and were followed by accessibility and design. Variable strength was tested on the basis of significance levels and intuitiveness of the coefficient in relation to magnitude and direction consistency. The variable list was then condensed to those that added significance to the model and were intuitive in relation to the greater context of the model. A manual process of finding the best subset of variables that limited multicollinearity was conducted to build the strongest fit of independent variables for each mode choice within the categorical dependent variable.

Results

The variables resulting in the strongest-fitting model were the same for the morning and the evening. Table 3 lists the variables, units, and outputs for each model.

These results show a large number of variables that are significant and intuitive for the individual modes. Variables that appeared as not significant were generally removed from the final model, although some nonsignificant but intuitive variables were retained. Table 4 lists the variables, units, and elasticities for each mode after the nonsignificant variables were filtered out.

"Elasticity" for each variable and mode choice is defined as the percentage change in the response variable with respect to a 1% change in an explanatory variable. On the basis of elasticities in the morning model, the distance from a site to the nearest Metrorail station had the greatest responsiveness with respect to the transit mode choice in the negative direction for both the morning and evening models, an intuitive result in that fewer transit trips may be taken with greater distance to a Metrorail station. The share of total employment that is within 45 min by Metrorail had the greatest responsiveness with the bike mode choice, which may indicate that propensity to bike is linked to the choice to live near transit. The variable for total parking units with respect to service population, the combined sum of employment and population, showed the greatest responsiveness with the bike mode choice in the negative direction, meaning that more parking may decrease bicycle ridership and induce auto use. Alternatively, those people most likely to drive may choose locations with parking provided. The variable for employment

TABLE 3 Summary of Mode Choice Model

Variable	Mode	Estimate	SE	*p*-Value	Significance
a.m. Peak Hour (log likelihood = −19,698; McFadden R^2 = 0.023788)					
Distance to Metrorail (ft)	Auto passenger	6.37 E−05	9.34 E−05	.495129	
	Bike	4.14 E−04	1.39 E−04	.002985	**
	Transit	−7.88 E−04	6.08 E−05	2.20 E−16	***
	Walk	−1.86 E−05	4.76 E−05	.696396	
Employment share within 45 min by Metrorail	Auto passenger	−1.26 E+00	1.74 E+00	.468617	
	Bike	9.39 E+00	2.55 E+00	.000229	***
	Transit	4.26 E+00	1.11 E+00	.000133	***
	Walk	3.96 E+00	9.00 E−01	1.11 E−05	***
Parking provided per service population	Auto passenger	−7.83 E−01	2.39 E−01	.001035	**
	Bike	−1.83 E+00	3.71 E−01	8.11 E−07	***
	Transit	1.65 E−01	1.41 E−01	.241656	
	Walk	−3.31 E−02	1.11 E−01	.765092	
Neighborhood population density	Auto passenger	−1.85 E−07	3.46 E−06	.957331	
	Bike	4.17 E−05	5.04 E−06	2.22 E−16	***
	Transit	1.07 E−05	2.12 E−06	5.06 E−07	***
	Walk	2.12 E−05	1.78 E−06	2.20 E−16	***
Employment within 1 mi	Auto passenger	−2.34 E−07	6.49 E−07	.718294	
	Bike	−1.05 E−06	9.67 E−07	.278974	
	Transit	−3.58 E−07	4.31 E−07	.405746	
	Walk	2.85 E−06	3.32 E−07	2.20 E−16	***
Mode constant	Auto passenger	−1.10 E+00	5.01 E−01	.027805	*
	Bike	−5.71 E+00	7.47 E−01	2.09 E−14	***
	Transit	−1.04 E+00	3.20 E−01	.001094	**
	Walk	−1.32 E+00	2.63 E−01	4.93 E−07	***

(continued on next page)

TABLE 3 *(continued)* **Summary of Mode Choice Model**

Variable	Mode	Estimate	SE	*p*-Value	Significance
p.m. Peak Hour (log likelihood = –26,867; McFadden R^2 = 0.023642)					
Distance to Metrorail (ft)	Auto passenger	–2.51 E–04	6.48 E–05	.000107	***
	Bike	3.83 E–04	9.08 E–05	2.40 E–05	***
	Transit	–7.54 E–04	5.35 E–05	2.20 E–16	***
	Walk	–1.25 E–04	3.97 E–05	.001605	**
Employment share within 45 min by Metrorail	Auto passenger	–9.54 E–01	1.26 E+00	.448633	
	Bike	5.98 E+00	1.75 E+00	.000658	***
	Transit	3.89 E+00	1.02 E+00	.000127	***
	Walk	5.15 E+00	7.78 E–01	3.38 E–11	***
Parking provided per service population	Auto passenger	1.35 E–01	1.51 E–01	.371292	
	Bike	–1.32 E+00	2.37 E–01	2.63 E–08	***
	Transit	–1.06 E–01	1.32 E–01	.420875	
	Walk	–8.58 E–01	1.01 E–01	2.20 E–16	***
Neighborhood population density	Auto passenger	1.72 E–06	2.58 E–06	.50564	
	Bike	3.20 E–05	3.67 E–06	2.20 E–16	***
	Transit	1.45 E–05	2.02 E–06	6.83 E–13	***
	Walk	2.82 E–05	1.59 E–06	2.20 E–16	***
Employment within 1 mi	Auto passenger	3.33 E–06	4.92 E–07	1.36 E–11	***
	Bike	1.98 E–06	6.83 E–07	.003797	**
	Transit	9.54 E–07	4.21 E–07	.023498	*
	Walk	4.19 E–06	3.10 E–07	2.20 E–16	***
Mode constant	Auto passenger	–8.83 E–01	3.54 E–01	.012652	*
	Bike	–4.16 E+00	5.07 E–01	2.22 E–16	***
	Transit	–9.66 E–01	2.83 E–01	.000649	***
	Walk	–9.05 E–01	2.20 E–01	4.06 E–05	***

****p*-value ≤ .01; ***p*-value ≤ .05; **p*-value < .1.

within 1 mi of the site was most positively responsive to the walk and bike modes, which may indicate that walking and biking increase with greater proximity to jobs.

Validation of Combined Person Trip and Mode Choice Model

Table 5 shows the results by mode for District DOT MXD+ when the person trip and mode choice models were applied in combination and the relative performance for auto and all person trips between the ITE *Trip Generation Manual* and District DOT MXD+, respectively.

Figure 1 displays scatter plots for District DOT MXD+ and ITE rates for auto and person trips for the morning and evening peak hours, respectively, and exhibits the robust results generated via District DOT MXD+.

CONCLUDING THOUGHTS AND MODEL APPLICATION

District DOT MXD+ consists of total person trips and mode choice models. First, person trips were calculated by a model utilizing variables for ITE trip rates and the density of auto-oriented intersections.

TABLE 4 Elasticities for Mode Choice Model

Variable	Source	Auto Passenger	Bike	Transit	Walk
a.m. Peak Hour					
Distance to Metrorail (ft)	D.C. Office of Planning	—	0.38	–0.60	—
Employment share within 45 min by Metrorail	MWCOG	—	2.29	0.86	0.55
Parking provided per service population	Data Collection	–0.29	–0.70	—	—
Neighborhood population density	MWCOG	—	1.12	0.24	0.32
Employment within 1 mi	MWCOG	—	—	—	0.13
p.m. Peak Hour					
Distance to Metrorail (ft)	D.C. Office of Planning	–0.22	0.36	–0.61	–0.06
Employment share within 45 min by Metrorail	MWCOG	—	1.43	0.80	0.59
Parking provided per service population	Data Collection	—	–0.50	–0.03	–0.15
Neighborhood population density	MWCOG	—	0.85	0.33	0.36
Employment within 1 mi	MWCOG	0.25	0.15	0.06	0.16

NOTE: Elasticities are included for statistically significant variables in each mode. MWCOG = Metropolitan Washington Council of Governments; — = data not included.

TABLE 5 Validation of District DOT MXD+

	Validation Statistic	Auto Vehicle Trips	Transit Trips	Walk Trips	Bike Trips	All Person Trips
a.m. Peak Hour						
DDOT MXD+	Average model error	4%	9%	4%	14%	5%
	R^2	0.66	0.63	0.67	0.46	0.67
ITE	Average model error	129%	NA	NA	NA	–40%
	R^2	0.60	NA	NA	NA	0.66
p.m. Peak Hour						
DDOT MXD+	Average model error	4%	8%	4%	5%	5%
	R^2	0.79	0.76	0.64	0.65	0.76
ITE	Average model error	169%	NA	NA	NA	–36%
	R^2	0.66	NA	NA	NA	0.66

NOTE: DDOT = District Department of Transportation; NA = not available.

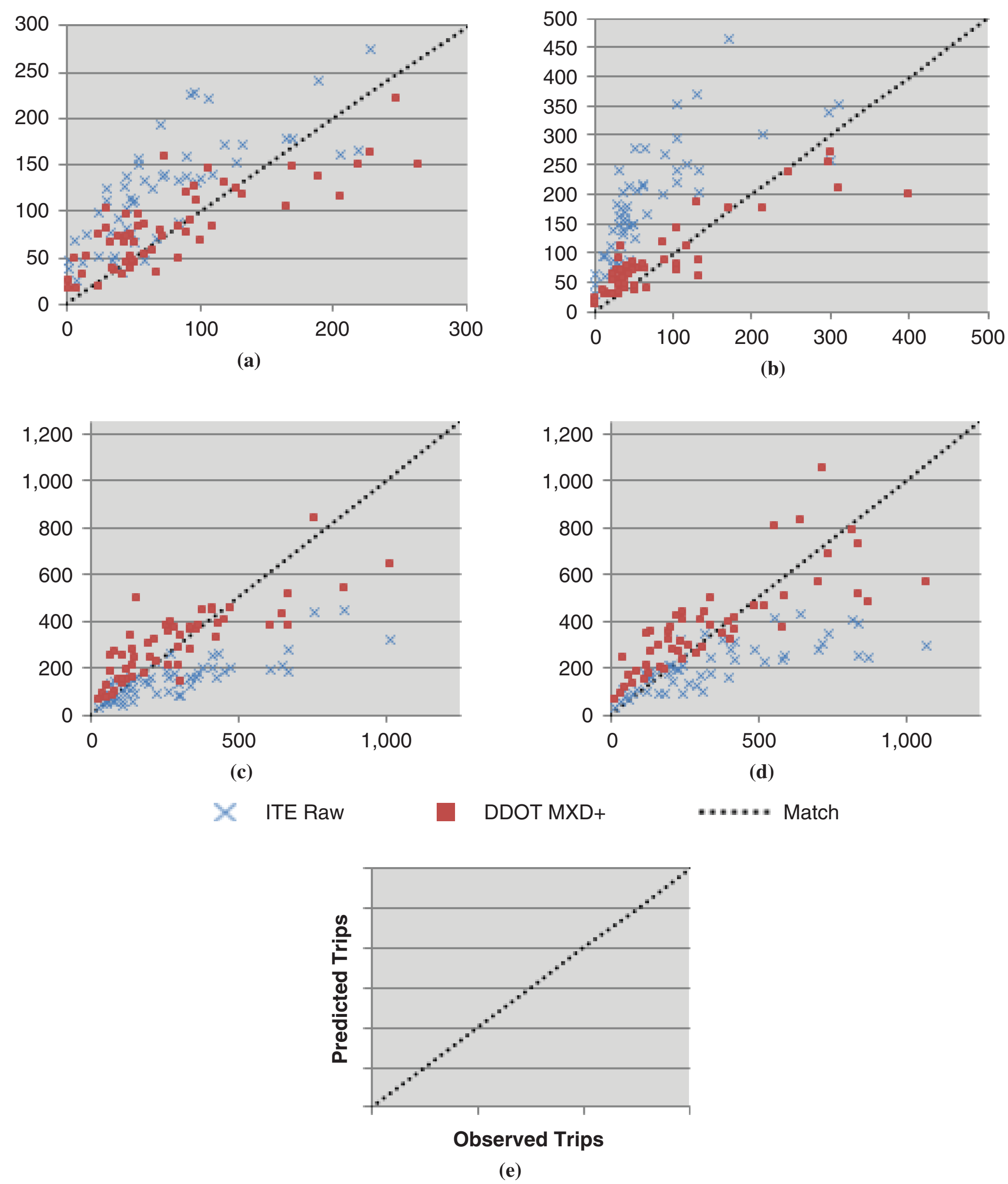

FIGURE 1 Comparison of results of District DOT model and ITE raw data: (*a*) auto trips, morning peak hour; (*b*) auto trips, evening peak hour; (*c*) all person trips, morning peak hour; (*d*) all person trips, evening peak hour; and (*e*) key to graphs.

Second, mode choice was calculated by a logit model that incorporated distance to a Metrorail station, employment share, employment, parking, and population density. Combining of the outputs from both models estimated trip generation by mode. The full set of models achieved better statistical performance by mode than ITE and other available existing research, and included sensitivity to local environment and on-site components. In addition, District DOT MXD+ was sensitive to the amount of parking provided on site, a major step forward in the understanding of how parking provisions influence travel behavior at a local-site level.

District DOT MXD+ is extremely valuable for more accurately estimating multimodal trips for proposed mixed-use residential urban buildings and brings a better understanding of the level of impact of a planned building. These benefits allow agencies to negotiate more accurately mitigations from developers on the basis of transportation system impacts. Person trip observations in Washington, D.C. were significantly (30% to 50%) higher than the limited person trip data presented in the ITE vehicle trip generation resources. Higher person trip making and high nonauto mode shares may indicate that more trips are made on foot with less trip chaining because of increased access to goods and services.

District DOT MXD+ addresses the limitations of the ITE approach in that it more accurately estimates auto demand at a proposed development and thus facilitates correct estimates of traffic and environmental impacts, including air quality and greenhouse gas emissions. Unlike ITE, District DOT MXD+ accurately estimates nonauto trips for improved infrastructure investment decisions that balance vehicular capacity expansion, including parking infrastructure, with investments for pedestrians, bicyclists, and transit infrastructure. Although a robust body of research on person trip models does not exist, District DOT MXD+ acts as a first step of progress in understanding the relationship between person trip generation and the urban context.

District DOT MXD+ is structurally simple and easily implemented into a usable tool. From the results of District DOT MXD+, a spreadsheet application was designed that District DOT will use during developmental review to confirm trip generation analyses from other parties.

NEXT STEPS

Next steps for the District DOT include opportunities for more-focused work on differentiating trip generation rates from varying types of urban retail destinations. District DOT MXD+ presented here is valid for residential-over-nonspecific-retail sites only. Exploration of variation among retail type could glean further trip generation guidance. Other types of sites, such as office, hotel, or retail only, may also show different travel behavior. In addition, possibly because of the homogeneity of the sites surveyed or a larger relationship in urban travel behavior, relationships were not found between trip making or mode share and socioeconomic factors. Furthermore, data used to derive District DOT MXD+ were collected predominantly in 2013 and 2014. Travel behavior in the District continues to change, most notably with the rise of transportation network companies such as Uber and Lyft, as well as the popularity of the bikeshare system.

The majority of the research on trip generation for mixed-use developments in urban settings has relied on pivoting from ITE-based estimates. The field of travel demand modeling contains a large library of research that involves the use of household travel surveys and other observed data to derive non-ITE-based trip generation models. These models are often abstracted for use in large regional travel models and do not contain explicit relationships to the built environment at a local scale. Future research should aim to converge models for local trip generation with models for regional travel demand model trip generation.

Further research should also investigate the factors within the ITE rates that are significant in relation to person trip generation. Factors such as employment and population accessibility, activity density, and diversity are likely candidates to be further explored. Other research in the realm of person trip generation may illustrate factors that could be included in future analyses.

Next steps should further consider the potential for exploring a model that does not pivot to person trips from vehicle trip generation rates in the ITE *Trip Generation Manual.* ITE is already undergoing a shift toward person trip generation, with the 10th edition of the Manual planned to have person trip generation rates and a call issued for person trip data. Several agencies, including ITE, the California Department of Transportation, the National Association of City Transportation Officials, and other jurisdictions, are doing research on urban person trip generation that could inform a direct person trip model.

Next steps for application of the model will include converting the spreadsheet tool into a web-based application, with more-advanced geographic information system capabilities, which will provide greater availability, transparency, and implementation and thereby democratize analysis similar to what the District DOT ParkRight calculator (http://www.parkrightdc.org/) does. This development would allow for a finer-grained level of analysis at the parcel level, as opposed to the current application, which conducts analysis on the basis of neighborhood-level characteristics. The web application would also allow for the public at large to investigate how trip generation varies by location within the District.

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