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A Literature Review: Improving How Active Transportation Demand is Modeled and Evaluated

A Research Report from the University of California Institute of Transportation Studies

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16. Abstract

Local transportation agencies typically rely on traditional travel demand forecasting models that focus on highway and roadway improvements to optimize vehicular traffic. These models are not equipped to evaluate active transportation strategies which align with current State of California policies such as reducing vehicle miles traveled to cut greenhouse gas emissions and fostering active transportation modes. In this context, ITS at UC Irvine (ITS Irvine) was invited by Orange County Transportation Authority (OCTA) to propose, develop, and apply an approach to better model active transportation. This report represents the first phase of this work, which is a review of the recent literature on how to model demand for active transportation and an examination of OCTAM's (OCTA's own regional travel demand model) Active Transportation (AT) modeling tool to evaluate its potential for modification or incorporation into a new active transportation model.

The following observations/suggestions are offered in this report: First, that OCTAM AT does not include variables that could impact people's decision to leave their vehicles at home in favor of transit. Second, a number of conditions need to be jointly met for people to walk or bike. Third, OCTAM AT does not capture residential self-selection, which could be important here as people who do not plan to walk/bike self-select into car-oriented neighborhoods.

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The University of California Institute of Transportation Studies (UC ITS) is a network of faculty, research and administrative staff, and students dedicated to advancing the state of the art in transportation engineering, planning, and policy for the people of California. Established by the Legislature in 1947, ITS has branches at UC Berkeley, UC Davis, UC Irvine, and UCLA.

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A Literature Review: Improving How Active Transportation Demand is Modeled and Evaluated

UNIVERSITY OF CALIFORNIA INSTITUTE OF TRANSPORTATION STUDIE

July 2017

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Executive Summary

Local transportation agencies have typically relied on traditional travel demand forecasting models that focus on highway and roadway improvements to optimize vehicular traffic. These models are not well-suited for evaluating newer active transportation strategies aimed at addressing current State of California policies such as reducing vehicle miles traveled to cut greenhouse gas emissions and fostering active transportation modes. Such strategies include: changing the composition and mix of land uses, building new sidewalks, reducing roadway speed, increasing the number of bus stops, and providing new bicycle lanes.

In this context, ITS at UC Irvine (ITS Irvine) was invited by Orange County Transportation Authority (OCTA) to propose, develop, and apply an approach to better model active transportation. This new active transportation model will support efforts to understand the travel behavior impacts of active transportation improvements and it will help OCTA prepare strategies to meet State of California requirements to reduce household vehicle travel and greenhouse gases emissions as part of SB 743. This report represents the first phase of this work, which is a review of the recent literature on how to model demand for active transportation and an examination of OCTAM's (OCTA's own regional travel demand model) Active Transportation (AT) modeling tool to evaluate its potential for modification or incorporation into a new active transportation model.

In light of the literature review and of general considerations about people's mode choices, we offer the following observations/suggestions:

1. First, we note that OCTAM AT does not include variables that could impact people's decision to leave their vehicles at home in favor of transit. These variables relate to economic conditions (such as gasoline prices, the median wage and the unemployment rate), perceptions (such as safety both from traffic and from crime), and the quality of both the biking network (e.g., see Broach & Dill, 2017), and walking routes (including pedestrian signals at major crossings) (Broach and Dill, 2016);
2. Second, a number of conditions need to be jointly met for people to walk or bike (e.g., existence of continuous sidewalks or a dense enough network of bike lanes, safety from both traffic and crime); in isolation, these conditions would not lead to people walking. One way to represent this dependence in statistical models is to use interaction terms; and
3. Third, OCTAM AT does not capture residential self-selection, which could be important here as people who do not plan to walk/bike self-select into car-oriented neighborhoods. One convenient tool to tackle this issue is generalized structural equations modeling (GSEM) (Kline, 2015). A well-specified GSEM model could incorporate a multinomial or a count model and include latent factors characterizing people's attitudes based on additional information while controlling for residential self-selection.

1. Introduction

In an effort to better understand demand for active transportation and to cost-effectively plan for related investments, the Orange County Transportation Authority (OCTA) has partnered with the Institute of Transportation Studies (ITS) at the University of California, Irvine, (UCI) to propose, develop, and apply an approach to model active transportation. Local transportation agencies have typically relied on traditional travel demand forecasting models that focus on highway and roadway improvements to optimize vehicular traffic. These models are not well-suited for evaluating newer active transportation strategies aimed at addressing current State of California policies such as reducing vehicle miles traveled to cut greenhouse gas emissions and fostering active transportation modes. Such strategies include: changing the composition and mix of land uses, building new sidewalks, reducing roadway speed, increasing the number of bus stops, and providing new bicycle lanes.

In this context, ITS at UCI has been invited by OCTA to propose, develop, and apply an approach to better model active transportation. This new active transportation model will support efforts to understand the travel behavior impacts of active transportation improvements and it will help OCTA prepare strategies to meet State of California requirements to reduce household vehicle travel and greenhouse gases emissions as part of SB 743.

This report covers work done during the first phase of this project, between the start of this project and June 2017. During that period, ITS conducted a selected review of the recent literature on how to model demand for active transportation and examined OCTAM's (OCTA's own regional travel demand model) Active Transportation (AT) modeling tool to evaluate its potential for modification or incorporation into a new active transportation model. This AT model was developed for OCTA by Fehr & Peers to increase OCTAM's sensitivity to active transportation investments and to allow for a more dynamic assessment of the costs and benefits that could be achieved by applying active transportation strategies within a community or region.

To conduct our literature review, we focused primarily on papers presented at the last two annual conferences of the Transportation Research Board (TRB) and we searched the Internet using Google Scholar for active transportation modeling studies that have become available on line over the past 4 years. We also used Google Scholar to trace studies that cited papers of interest to broaden our search.

In Section II, we give a brief overview of key California laws (AB 32, SB3 75, and SB 743) to provide some background about the greenhouse gas emissions targets and sustainable forms of transportation goals that are driving OCTA's efforts.

In Section III, we review selected active transportation case studies. Our search returned three papers that focus on California – including two in Los Angeles County. We summarize findings and describe which of the strategies available to OCTA (land use change, new sidewalks, roadway speed restrictions, or new bicycle lanes) these papers focus on. The remaining papers analyze other regions in the U.S. (i.e. Pacific Northwest, Rocky Mountains, Midwest, East Coast, and the South) or abroad.

In Section IV, we review selected papers based on how they analyze and model active transportation. Our search returned five papers that use four-step models (or data derived from those models) to answer research questions related to active transportation. Since the OCTAM AT Module is a multinomial logit model, we paid particular attention to studies that use a similar approach and summarize six such studies. Other published papers use a range of models, including count models (such as the negative binomial model) or linear regression to estimate counts, and some hybrid or less common methodologies (such as qualitative interviews, structural equation models, or queueing models). Given space constraints, we focus on the types of questions answered by each method, and the relationship of each study to the four strategies available to OCTA. The research questions and findings of individual papers mentioned below are available in the paper summaries provided in Appendix A.

In Section V, we give a brief overview of the active transportation module in OCTAM, discuss some input parameters, and explain why comparing the coefficients of the OCTAM AT Model with the California/multinomial logit case studies referenced in our literature review is not possible. A summary of the values of the coefficients in these comparison studies is available in Appendix B.

Finally, Section VI concludes and presents some suggesting for moving forward, contingent on funding for the second phase of this project.

2. California Legislation Summary

In this section, we very briefly review three California laws – AB 32, SB 375 and SB 764 - that impact how sustainability can be incorporated in transportation policy.

2.1 AB 32: The Global Warming Solutions Act of 2006

Assembly Bill 32 (AB 32) was signed into law on September 27, 2006 and mandates that California reaches 1990 levels of greenhouse gas (GHG) emissions by 2020, which represents a twenty-five percent decrease from current GHG levels (Center for Climate and Energy Solutions).

The main components of AB 32 are: 1) the creation of a cap-and-trade mechanism; 2) an increase in fuel efficiency of motor vehicles; 3) a decrease in the carbon content of fuels; and 4) measures to motivate communities to become more energy efficient. Since its implementation in 2006, AB 32 has facilitated the passage of a cap and trade program in 2010, which placed an upper limit on GHG levels emitted in the state of California.

AB 32 covers the major GHGs emitted into the atmosphere (California Air Resources Board, 2014). The scoping plan required by AB 32 outlines what actions will be taken to reduce the emissions of GHG from different sources and how particular regulations and strategies or plans can contribute to this goal. AB 32 also identifies the levels of emissions, sets feasible limits, and requires the mandatory reporting of these emissions.

2.2 SB 375: Sustainable Communities and Climate Protection Act of 2008

Senate Bill 375 (SB 375) was passed to help meet the environmental goals set out by AB 32. SB 375 aims to reduce: the amount of carbon emitted by motor vehicles, the amount of carbon in fuel, and vehicle miles traveled (VMT). Under the SB 375, the Air Resources Board (ARB) sets regional targets for GHG emissions reductions from passenger vehicles. In 2010, ARB established these targets for 2020 and 2035 for each region covered by one of the State's MPOs.

Each of California’s MPOs must prepare a "sustainable communities strategy" (SCS) as an integral part of its regional transportation plan (RTP). The SCS covers land use, housing, and transportation strategies. Its measures should allow each MPO to meet its GHG emission reduction targets (California Air Resources Board, 2016). Once adopted by an MPO, the RTP/SCS guides transportation policies and investments. ARB must review each SCS to confirm that the SCS, if implemented, would meet regional GHG targets. If the combination of measures in the SCS will likely not meet regional targets, the MPO must prepare a separate “alternative planning strategy" (APS) to meet these targets.

The Sustainable Communities Act also establishes incentives to encourage local governments and developers to implement their local SCS or APS. Developers can get relief from some environmental review requirements under the California Environmental Quality Act (CEQA) if their new residential and mixed-use projects are consistent with a region's SCS/APS.

2.3 SB 743: Updating Transportation Metrics in CEQA

Passed on September 27, 2013, Senate Bill (SB 743) requires the Governor's Office of Planning and Research (OPR) to amend the CEQA Guidelines to provide an alternative to Level of Service (LOS) for evaluating transportation impacts. It directs OPR to recommend alternative metrics, such as vehicle miles traveled (VMT) or trip generation rates, as thresholds of significance. The overarching goal of SB 743 is to balance congestion management with statewide goals promoting infill development, public health through active transportation, and reductions of greenhouse gas emissions.

Once the CEQA Guidelines are amended to include those alternative criteria, automobile delays will no longer be considered a significant impact under CEQA. However, transportation impacts related to air quality, noise, and safety must still be analyzed under CEQA where appropriate. SB 743 also amends congestion management law to allow cities and counties to opt out of LOS standards within certain infill areas.

Aside from changes to transportation analysis, SB 743 includes several important changes to CEQA that apply to transit oriented developments, including aesthetics and parking. Parking impacts will not be considered significant impacts on the environment for select development projects within infill areas with nearby frequent transit service.

3. Summary of Selected Active Transportation Studies

3.1 California

Our literature search returned three papers dealing with California: Brozen et al. (2017), who focus on four California Metropolitan Planning Organizations (MPOs); Ravulaparthy et al. (2017), who analyze Los Angeles County, CA; and Macias (2016), who focus on the Expo Line in Los Angeles.

The October 19, 2016 OCTA letter of understanding between OCTA and ITS mentions four strategies available to OCTA to promote active transportation: land use change, new sidewalks, roadway speed restrictions, and new bicycle lanes. Ravulaparthy et al. (2017) are concerned mostly with bicycle infrastructure. Their main goal is to create a toolbox of statistical models to 1) estimate the propensity and frequency of recreational travel; and 2) allocate recreational trips to individual bicycle facilities. Their propensity model (a binary logit model) accounts for the density of different types of bike trails around transit stations, and their allocation model (a utility function) accounts for the type of bike trails. They report that both the incidence of treated bicycle facilities and the presence of a bike share program increase bicycling - a result that has implications for new bicycle lanes and for other facilities aiming at promoting active transportation.

The other two studies do not model active transportation mode shares, but their research questions and results should be of interest to transit operators.

Macias (2016) compares different methods to define catchment areas for rail stations. These methods have implications for exploring land use change as a strategy although this paper does not model mode shares. Macias (2016) compares three new approaches against two traditional approaches for 12 stations along the Expo Line in Los Angeles. The new approaches are the network grade, pedestrian speed, and pedestrian energy methods. The traditional approaches are the Euclidean distance and network distance methods. Macias applies spatial analysis tools in Geographic Information Systems (GIS) software, followed by single-factor ANOVA to compare these five approaches. Results show that these methods generate catchment areas of significantly different sizes. One consequence is that a simple Euclidian approach (Method 1) for pedestrian catchment can mislead planners into investing in streets not accessible by transit.

Brozen et al. (2017) is the only paper in this review that uses long-form interviews (a qualitative methodology). Rather than modeling mode share for walking, the authors explore MPOs' perceptions of their ability to model walking as a mode based on 45 minute interviews with two staff members (one directly involved with modeling and one who uses model output in planning applications) at four California MPOs to identify improvements for the next generation of activity-based regional travel demand models. They report four findings: 1) Household travel surveys tend to underestimate walking; 2) MPOs lack an inventory of the walking network and the quality of pedestrian infrastructure, and thus have difficulty pinpointing locations for pedestrian network improvements; 3) Regional travel demand models are not well suited to understand the factors necessary to induce or improve walking; and 4) The limited data on the geography of walk trips inhibits model calibration and identification of walking volumes at specific intersections or corridors.

3.2 Other US Studies

3.2.1 Portland, OR and the Pacific Northwest

Our literature search returned six papers whose study areas are either in Portland, OR, or in the Pacific Northwest. Of these, three papers estimate multinomial models: Broach & Dill (2016) to model bicycle route share, and Clifton et al. (2016a-b) to model pedestrian mode share. Clifton et al. (2016a-b) use data from four-step models.

Zimmermann et al. (2017) propose a link-based bike route choice model that overcomes variability in estimating route choices in Eugene, OR. Their results emphasize the sensitivity of cyclists to distance, traffic volume, slope, crossings and presence of bike facilities. Fagnant and Kockelman (2016) develop a direct-demand model for estimating peak-period cyclist counts in the Seattle, WA, metropolitan area. Their results show that wider bike lanes and curb lanes, along with lower traffic volumes, create favorable conditions for a higher numbers of cyclists.

Clifton et al. (2016a-b) model destination choice behavior of pedestrians in an attempt to represent pedestrian activity more effectively with applications to Portland, OR. Clifton et al. (2016a) report that distance is a significant deterrent to pedestrian destination choice; although people in carless or childless households are less sensitive to distance for some trip purposes. Clifton et al. (2016b) include a proof-of-concept application for representing pedestrian activity.

Broach and Dill (2017) develop linear regression models to predict the impact of various network and land-use changes on bicycling in the Portland, OR, area. They find evidence that network quality matters not only in deciding where to bike, but also whether to bike. In an earlier paper, Broach and Dill (2016) estimate a multinomial logit route choice model to approximate least-cost cycling paths for trips taken between 2010 and 2013. For cycling, excess distance, upslope, motor vehicle traffic, and specific bicycle infrastructure all have significant and similar effects on route and mode choice decisions. For pedestrian choices, quality walking routes and pedestrian signals at major crossings attract pedestrians from alternative routes and increase the odds of walking on a trip.

3.2.2 Rocky Mountains and the Midwest

Five papers study areas in the Rocky Mountains or in the Midwest. Of these papers, Bernardin & Chen (2016) analyze data from the Salt Lake City, UT, area four-step model, while Marshall & Henao (2015) consider data from a Denver, CO, region activity-based model. In addition, Marshall & Henao (2015) estimate a multinomial logit discrete choice model.

Bernardin & Chen (2016) aim to develop linear regression models that improve the accuracy and response properties of non-home-based trips in trip-based models. Using the Wasatch Front Regional Council (WFRC) four-step model, the authors achieve reasonable responses to hypothetical new residential growth, and plausible mode shifts in response to hypothetical enhancements in transit service.

Li et al. (2016) rely on a hybrid approach to model the impact of different land use types on pedestrian trip generation, frequency, and distance in the Salt Lake City metro area, They report that the following factors positively influence the propensity and frequency of pedestrian travel: household size, land use mix, the presence of non-residential destinations, and street connectivity.

Marshall & Henao (2015) explore resiliency, vulnerability, and transportation affordability issues via a multinomial logit model estimated on data from the Denver, CO, metro area. Their model incorporates driving cost, distance to downtown or employment, transit infrastructure characteristics, and measures of traveler behavior. Their results suggest that while higher resilience is associated with proximity to employment, to compact and connected street networks, and to better transit infrastructure, merely being a public transit user is not as important to resilience as living near better transit infrastructure.

Hankey & Lindsey (2016) present facility-demand models based on peak period (4 to 6 pm) counts of pedestrian and bicycle traffic in Minneapolis, Minnesota. They find that reduced-form models perform nearly as well as fully specified models and are easier to apply and interpret. In an earlier paper, Hankey et al. (2012) summarize counts of cyclists and pedestrians between 2007 and 2010, also in Minneapolis, MN. Their results suggest that when controlling for factors such as land use mix and street (or bicycle facility) type, bicycle traffic increases over time and is higher on streets with bicycle facilities than without.

3.2.3 East Coast and the South

Six of the papers we found study areas on the East Coast or in the South. Reardon et al. (2017) estimate a multinomial logit model. Two other papers - Davis & Leven (2016) and Garikapati et al (2017) - analyze data from their respective regions' four-step models.

Garikapati et al. (2017) are interested in estimating household travel energy consumption in the Atlanta, GA, metropolitan area using information readily available from standard four-step travel demand models. Results show that a household's travel energy footprint is strongly correlated with population density.

In Blacksburg, VA (a small, rural college town), Lu et al. (2017) consider a comprehensive bicycle and pedestrian traffic monitoring campaign that could be scaled to monitor active transportation traffic flows across larger urban areas. Their models exhibit strong correlation with observed validation counts.

Davis & Leven (2016) analyze six Washington, DC, metro region scenarios to explore whether land use and other regionally applied policies may be sufficient to handle projected growth. More details on the findings of this complex study are given in the subsection "Studies using four-step models or their data". Meanwhile, Kim & Susilo (2013) analyze National Household

Travel Survey (NHTS) data to construct various pedestrian trip generation models for the nearby Baltimore region. Their results suggest that in practice, Poisson Regression Modeling (PRM) can provide a better model fit between the base and estimated models - despite the theoretical advantages of negative binomial regression models for handling over-dispersed data.

Steinmetz-Wood et al. (2017) apply a cross-classified multilevel logistic regression to 14,773 Massachusetts travel survey respondents, to investigate how the size and scale of census units influence the relationship between land-use mix and active transportation to work. Their results show that correcting the area consistently increases the odds ratio of using active transportation, although the size and significance of the land-use mix odds ratio varies with geographical scale.

Meanwhile, Reardon et al. (2017) estimate latent demand for pedestrian and bicycle travel by calculating Network Utility Scores for the entire Massachusetts local roadway inventory (49,116 miles). This metric could be a helpful tool for identifying links for new or improved pedestrian and bicycle facilities (two strategies available to OCTA).

3.3 US National Datasets

Two of the papers we found during our literature search analyze national (rather than regional) data: Jamali & Wang (2017), and Lugo & Srinivasan (2016).

Jamali & Wang (2017) analyze National Household Travel Survey (NHTS) data with a focus on rural and small urban areas in nine states. They specify a negative binomial regression model to estimate household-level pedestrian exposure for rural and small urban settings. Their model accounts for household characteristics (e.g., income and vehicle ownership), region of the country, and block-group-level attributes (e.g., population density and school density).

Lugo & Srinivasan (2016) use data fusion techniques to match American Time Use Survey Eating and Health Module (ATUS-EH) records with NHTS records. They estimate linear regression to model the relationship between health and multi-modal long-term travel choices. They find that biking has no statistically significant impact on either Body Mass Index (BMI) or Self-Assessed Physical Health Score (SAPHS). They also report that pedestrians who walk 4-5 walking trips/week have a lower BMI and feel better than those with more than 6 walking trips/week. In comparison, transit users (2-3 trips/month) have a lower BMI compared to others, but those who take more than 2-3 trips transit trips/month are generally happier with their health than those with fewer than 2 transit trips / month. Finally, those who drive between 5,000-15,000 miles a year have a lower BMI than those who drive more.

3.4 International Case Studies

3.4.1 Canada

We found seven papers whose study areas are in Canada. Four of these focus on the Greater Toronto area. Only Hasnine et al. (2017) use a multinomial logit discrete choice model. None of the other papers use four-step models.

Hasnine et al. (2017) estimate multinomial, nested, and cross-nested logit models to describe the mode choice behavior of post-secondary students commuting to school in Toronto. Their results suggest that female students who travel towards downtown are more transit and active mode oriented than those who travel away from downtown. This study also shows that the ownership of mobility tools (i.e., transit pass, car, and bike ownership) and age groups are significant variables in a student's mode choice. More details on this study can be found in Section IV.

Colley & Buliung (2016) analyze Canadian Transportation Tomorrow Survey (TTS) data. They generate descriptive statistics on the gender gap in mode choice in the greater Toronto and Hamilton areas. They report that: 1) Female children are driven to school more frequently than males, although working-age males drive more than females; 2) The gender gap in active transportation, public transit, and automobile use appears to be smaller today than in the mid-1980s; 3) The following factors are associated with the largest differences in driving between full time-employed women and men: having one vehicle per household, more than six household members, and living and working in the city of Toronto.

Idris et al. (2015) estimate an unspecified discrete choice model to investigate the over-prediction of public transit ridership by traditional mode choice models in the Toronto metropolitan area. Their primary contribution is to incorporate revealed preference (RP) data into their model. They report that traditional RP data-based mode choice model has a high tendency to over-predict transit ridership (by up to 134%).

In another Toronto studies, Habib et al. (2014) estimate an ordered probit model to estimate trip generation for pedestrian commuting. They find that average auto ownership at the zonal level is more influential than household auto ownership. However, their paper is not optimistic about the application of land use changes: "The empirical models reveal that the baseline walking propensity and distance remain unchanged over the years despite significant efforts to encourage active transportation through mixed land-use policies in the Greater Toronto and Hamilton Area."

In Vancouver, BC, Osama et al. (2017) rely on Bayesian analysis to develop zone-level ridership models and evaluate the impacts of network indicators, land use, and road facility on bike kilometers traveled (BKT). They find that more connected, dense, flat, continuous, recreational, and off-street bike networks yield higher BKT. In addition, models that account for spatial effects fit better than those that do not, which underscores the importance of considering spatial effects for modeling BKT.

In Montreal, QC, Loong & El-Geneidy (2016) estimate log-linear regression models to understand the amount of additional time commuters allocate to travel time unreliability. Their results reveal that while drivers allocate the most extra time for their commute, users of other modes (including transit and active transportation modes) budget 29% to 66% less extra time than drivers.

In Halifax, NS, Fatmi & Habib (2016) develop a panel-based random-parameters logit model to predict individuals' commuting mode choice over their lifetime. Their model includes access to the nearest park area, and a land use mix index. Their results show that: 1) High-income individuals tend to be car loyal; 2) No car ownership over the lifetime and the addition of a job increase the probability of transit loyalty; 3) Individuals with no children and who reside in an area with high walking and bike use have a higher probability of being loyal to active transportation; 4) A decrease in household income and tenure transition from owned to rental are likely to trigger a transition from car to transit; however, 5) the presence of children and the addition of a car increase the transition propensity from transit to car use.

3.4.2 Europe

We found three European studies in our literature search. None of these analyzes mode choice or uses four-step models, but their results have potentially useful applications for modeling active transportation modes.

For the Greater Copenhagen area, Ingvardson et al. (2017) estimate a Structural Equation Model for habitual travel behavior based on survey data. Their results support the hypothesis that habit formation derives from recurrent choices and from satisfying functional, relatedness and growth needs. For example, higher satisfaction with a mode (such as an active transportation mode) relates to a higher frequency of using that mode. Higher bicycle satisfaction relates positively to self-identification as a cyclist, and negatively as a driver. Greater car use satisfaction increases with self-identification as a driver and with perceived difficulties in using transit. Conversely, car use satisfaction decreases with difficulties in car use, and also decreases with the perception of oneself as being an effective cyclist. Higher transit satisfaction mainly relates to experiencing difficulties with other modes.

Gast et al. (2015) study the difficulty of forecasting the future availability of bicycles in stations of the Paris (France) Vélib bike-sharing system (BSS). They estimate Markovian queueing models to generate forecasts for each station. This novel approach allows planners to construct a probability distribution of the state of a station, whereas previous work focused on point estimators only.

In Dublin, Ireland, Doorley et al. (2014) examine a segregated bicycle lane in order to test the short-term forecasting accuracy of Bayesian structural time series models applied to continuous observations of cyclist traffic volumes. Their results show that peak period 1-step and multi-step forecasts for morning and evening rush hour periods are relatively accurate. However, they note that further studies are required to test the prediction accuracy across different locations with varying traffic conditions.

3.4.3 International Datasets

Our literature search returned a paper that analyzes an international dataset. Mjahed et al. (2015) estimate a structural equations model to analyze data from an online attitudinal survey fielded in July 2014 that received 207 responses from across the world Their results suggest that the determinants of walking differ based on the region of residence. The implication is that transportation policies may affect an individual's mode choice not only during childhood, but throughout his/her life cycle.

4. Approaches to Model Active Transportation

4.1 Studies Using Four-Step Models or their Data

A review of the selected studies that use four-step models sheds insights on the potential for modifying or incorporating OCTAM into a new active transportation model. Our literature search found five studies which either use four-step models or analyze their data: Bernardin & Chen (2016) for Salt Lake City, UT; Garikapati et al. (2017) for Atlanta, GA; Davis & Leven (2016) for Washington, DC; and Clifton et al. (2016a-b) for Portland, OR.

The October 19, 2016 OCTA letter of understanding mentions four strategies available to OCTA to promote active transportation: land use change, new sidewalks, roadway speed restrictions, and new bicycle lanes. The models in the studies above account for land use change and pedestrian infrastructure, but not roadway speed restrictions or bicycle infrastructure. None of these studies are in California.

The linear regression models in Bernardin & Chen (2016) may be able to model changes in land use: among its four validation tests, two scenarios include new residential and new commercial development. Garikapati et al. (2017) use density of the built environment as an input to their household travel energy calculations. Davis & Leven (2016) model six scenarios that cover a range of policies: one scenario holds land use forecasts constant, another scenario allows land use to shift within jurisdictions, and another allows shifting across jurisdictions. The multinomial logit discrete models in Clifton et al. (2016a-b) both contain independent variables that relate to land use mix and pedestrian facilities. However, these models, while similar, are not identical. These studies explore a wide variety of research questions and yield different results.

Bernardin & Chen (2016) develop models to improve the accuracy and response properties of non-home-based (NHB) trips in trip-based models. Their models achieve reasonable responses and mode shifts in response to hypothetical residential growth and enhanced transit service, and better replicated observed NHB trip rates, mode shares, and OD patterns.

One key research goal of Garikapati et al. (2017) is to use information readily available from standard four-step travel demand models in calculating TAZ-level household travel energy consumption. The authors also suggest procedures for calculating energy footprint in three situations: 1) when a four-step travel demand model exists; 2) when an activity-based model exists, and 3) when neither exists. Their key result is a strong correlation between travel energy footprint and the density of the built environment.

Clifton et al. (2016a-b) create frameworks to incorporate pedestrian activity in four-step models. Clifton et al. (2016a), who are interested in the impact of destination choice on pedestrian travel behavior, find that a 1.0 mi (1.6 km) increase in network distance to a particular destination yields an ~80% decrease in the odds of choosing that destination. They also report that sensitivity to distance varies according to trip purpose, traveler characteristics, and built environment characteristics. In contrast, Clifton et al. (2016b) focus on a proof-of-concept application to forecast pedestrian demand across an entire metropolitan region. Their framework improves travel model sensitivity to pedestrian-relevant factors, socio-economic changes, and policy interventions such as smart-growth strategies and pedestrian infrastructure investments.

Davis & Leven (2016) explore whether land use and other regional policies could handle projected forecast growth in the Washington, DC, metro region. To this end, they develop a somewhat unconventional methodology: they couple the regional four-step model with a postprocessor module, and iterate the two to achieve solutions on several measures of effectiveness including daily Metrorail ridership and daily transit mode share. Davis & Leven find that locating people and jobs in mixed-use areas with good transit access increases transit ridership and decreases vehicle miles traveled. Moreover, increasing the mix of uses in activity centers increases reverse commutes. Their findings also suggest that small changes (e.g. expanding park-&-ride capacity and walk & bike access, reducing fares for reverse commutes) do not significantly shift outcomes if land use is unchanged. In addition, while disincentives to driving (e.g. a cordon charge) positively affect a number of measures, they may not be necessary to increase transit ridership.

4.2 Multinomial Logit Models

The OCTAM Active Transportation Module is a multinomial logit discrete choice model (Fehr & Peers, 2016). Our literature search returned 6 studies that rely on multinomial logit discrete choice models: Hasnine et al. (2017) for Toronto, Canada; Reardon et al. (2017) for the Commonwealth of Massachusetts; Broach & Drill (2016) and Clifton et al. (2016a-b) for Portland, OR; and Marshall & Henao (2015) for Denver, CO.

The models in Hasnine et al. (2017) do not have explanatory variables that relate to the four strategies available to OCTA, so their work is less of interest here. They build multiple types of logit models (multinomial, nested, and cross-nested) to describe the mode choice behavior of post-secondary students commuting to school in Toronto.

The other five papers collectively cover three of the four strategies available to OCTA to promote active transportation: land use change, new sidewalks, and new bicycle lanes. Roadway speed restriction is not covered. Among these 6 studies, only Clifton et al. (2016a-b) use data from four-step models; their work should be of particular interest as they are primarily concerned with the destination choice behavior of pedestrians.

The multinomial logit models in Clifton et al. (2016a-b) and Marshall & Henao (2015) include a number of land use explanatory variables: TAZ area size (employment by type, households), the presence of parks, and land uses that provide barriers to walking (e.g. industrial-type employment) in Clifton et al. (2016a); and network distances from the Denver Central Business District, the Denver Tech Center, and Downtown Boulder; as well as the ratio of employees to population in Marshall & Henao (2015). Marshall & Henao's model also includes built environment variables such as intersection density, link-node ratio, population density, and employment density.

The models in Clifton et al. (2016a-b), Marshall & Henao (2015), and Reardon et al. (2017) incorporate variables related to sidewalks and pedestrian facilities. In Clifton et al. (2016a-b), these variables include an original Pedestrian Index of the Environment (aptly called “PIE”), walk trip distance, and terrain variables. Marshall & Henao (2015) is less direct: sidewalk improvements would have to be reflected by their built environment variables such as intersection density and link-node ratio. Reardon et al. (2017) also incorporate pedestrian facilities indirectly, via a WalkScore™ variable. However, their “network utility score” could be useful to OCTA for identifying and targeting links for new or improved pedestrian and bicycle facilities as it is a measure of latent demand for bicycle and pedestrian travel.

For biking, the work of Broach & Dill (2016), who are interested in predicting bicycle mode share as a function of network connectivity and quality, should be of interest. Their model contains a “mean route quality index” where network distances are weighted by quality. Ideal routes in their model are made up of links with low traffic or with a bike lane, without intersection delays, and with separated facilities on any river crossings. Negative factors along a route increase the quality-weighted distance and thus make the route less desirable; these negative factors include steep grades, heavy mixed traffic, frequent turns, or difficult intersections. Other model variables are related to the presence of jobs within 1-5 miles of the route, and demographic variable such as education, age, and income.

These five papers report a variety of findings. Broach & Dill (2017) find evidence that network quality matters not only in decisions of where to bike, but also whether to bike; network quality appears to have nearly 3 times the expected effect on bike commuting than does job access alone. Reardon et al. (2017) calculate network utility scores for the entire 49,116 miles of the local roadway inventory of the Commonwealth of Massachusetts. The findings of Clifton et al. (2016a-b) are discussed in sub-Section IV.1. Finally, Marshall & Henao (2015) find that being a public transit user does not seem to make as big a difference as does living near better transit infrastructure. Nonetheless, the authors find higher resilience in locations with proximity to high levels of employment, with more compact and connected street networks, and with better transit infrastructure.

4.3 Other Methods

This sub-Section provides a brief overview of the other methods that have been used to explore active transportation research questions. For brevity, we report mostly how each study relates to the four strategies available to OCTA to promote active transportation: land use change, new sidewalks, roadway speed restrictions, and new bicycle lanes.

Our search returned two literature reviews on active transportation topics. Currans (2017) identifies gaps in the state-of-the-art trip generation methods. The author finds that the literature understands the influences of the built environment on vehicular trips, but not necessarily on multimodal trips. Additionally, the literature shows little understanding about the influences of the trip-maker sociodemographic variables on behavior. This may lead to over- or under-estimating vehicle travel on either end of the income distribution.

Jamali & Wang (2017) categorize pedestrian exposure metrics into four general categories: area-based measures, point-based measures, segment-based measures, and behavioral attitudes of walk trips. Their own negative binomial-based pedestrian exposure metric has the household as its unit of analysis.

4.3.1 Other Discrete Choice Models

Multinomial logit models are not the only type of discrete choice models used in the papers we found.

Ravulaparthy et al. (2017) estimate a binary logit model to quantify riders' propensity to choose biking as a transportation mode within Los Angeles County. This model includes independent variables for the density of different classes of bicycle facilities so it is sensitive to the introduction of new bike lanes (a strategy available to OCTA).

Hasnine et al. (2017) compare a multinomial logit model with both a nested logit and a cross-nested logit model. The authors are concerned with modeling mode choice among post-secondary students commuting to four different Toronto area universities. Variables reflect more commuter characteristics than land use or infrastructure changes.

In Halifax, Canada, Fatmi & Habib (2016) develop a panel-based random-parameters logit model to model commute mode choice of individuals dynamically over their lifetime. Their variables focus on individual characteristics rather than on land use or infrastructure.

In an earlier study, Habib et al. (2014) build an ordered probit model to investigate trip generation for walking as a commuting mode. Their model variables include household characteristics, individual characteristics, nature of the trip, means of travel, and aggregate zonal land use and population data. While their model includes land use variables (and would thus be sensitive to any land use changes available to OCTA as a strategy), the authors are not optimistic about that approach. They note that "baseline walking propensity and distance remain unchanged over the years despite significant efforts to encourage active transportation through mixed land-use policies in the Greater Toronto and Hamilton Area."

Two other recent studies estimate logit models to study bike route choice rather than mode choice. Zimmerman et al. (2017), in their recursive logit bike route choice model, demonstrate the sensitivity of cyclist route choice to their bike facilities, distance, traffic volume, slope, and crossings variables. In contrast, Steinmetz-Wood et al. (2017) estimate a cross-classified multilevel logistic regression model not only to model the relationship between land use mix and active transportation, but also to examine the influence of geographical size and scale of census units on this relationship. Their model includes an independent variable for land use mix, and it is thus potentially sensitive to changes in land use.

4.3.2 Negative Binomial Regression Models (NBRM)

We found six studies that rely on negative binomial regression models tend to model trip generation and count pedestrians and/or bicycles. Unfortunately, none of these six studies focuses on California.

The pedestrian count model in Jamali & Wang (2017) includes block-group-level variables for school density, roadway centerline-mile density, and intersection density. Li et al. (2016) estimate pedestrian trip choice and frequency models using detailed bike lane infrastructure data managed in GIS. In their pedestrian and bicycle count models, Lu et al. (2017) select sites by street functional class, centrality of origins and destinations, and future bicycle facility buildout plans. The bicycle count models of Fagnant & Kockelman (2016) account for bike lane width and the presence of curb lanes.

Some NBRM studies also analyze land use policies. For example, Li et al. (2016) include a "land use mix" variable that positively influences the propensity and frequency of walk trips. Kim & Susilo (2013) use MD Property View 2001 and MD Transit View 2001 (programs published and managed by the Maryland Department of Planning) to obtain values for the land-use variables in their models.

Meanwhile, models in Hankey et al. (2012) incorporate variables that cover land use and facilities for both bicycle and pedestrian travel. Their land use include area of paved parking, retail and industrial land use, population density, and residential addresses, as well as meters of sidewalk and meters of on-street bike lanes.

4.3.3 Linear Regression Models

The linear regression models in the seven papers we found in our literature search are mostly used to estimate trip frequency, for both walking and biking. Of these seven papers, only Ravulaparthy et al. (2017) study an area in California (Los Angeles County).

Models in three papers include variables related to the composition and mix of land use. The land use variables in Broach & Dill (2017) mainly pertain to the number and proportion of jobs within 1-5 miles of a bicycle trip-generating Census Tract. The models in Bernardin & Chen (2016) underwent four sensitivity validation tests and include variables for new residential and commercial development. The stepwise linear regression models in Hankey & Lindsey (2016) (which are used for creating demand models for pedestrian and bicycle traffic) allow varying the spatial scale of land use variables in addition to transportation variables.

Both pedestrian and bicycle count models in Hankey & Lindsey (2016) also include variables related to sidewalks and to bike lanes. In contrast, the "network changes" variables in Broach & Dill (2017) consider bike lanes, but not sidewalks. In Ravulaparthy et al. (2017), both the propensity and the allocation models include variables for the density and type of bike trails around transit stations.

The linear regression model for trip frequency in Lugo & Srinivasan (2016) relies on data from the National Household Travel Survey, and does not include variables related to land use mix or pedestrian and bike facilities. Li et al. (2016) rely on linear regression to estimate average walking distances but they estimate negative binomial regression for trip choice and frequency. Their models include both bike lane infrastructure and land use data such as employment and residential counts.

Rather than using linear regression for counts (which would be a questionable choice), Loong & El-Geneidy (2016) use log-linear regression to estimate the amount of additional time that commuters around Montreal, Canada, allocate to account for travel time unreliability. Their log-linear model has variables for personal and trip characteristics, time, mode satisfaction, and home selection, but none relating to land use or to the presence of sidewalks and bike lanes.

4.3.4 Structural Equation Models

Two papers, both international case studies, estimate structural equation models (SEM). They are of interest for their strength in analyzing subjective experiences of preferred mode choices.

Ingvardson et al. (2017) construct a model for habitual travel behavior and habit formation. Active transportation modes include both walking and biking. Their survey questions include rating statements such as “I feel good about contributing to the environment when I bike” on a scale. Mjahed et al. (2015) focus on the influence of childhood experiences on adult walking behavior. Their survey includes similar survey statements to be rated on a scale: “Before high school my parents felt it was unsafe for me to use public transport” and “Before high school my parents felt it was unsafe for me to walk to my destinations.”

4.3.5 Hybrid Methods

Four of the papers discussed so far use more than one method to study active transportation. Of these, only Ravulaparthy et al. (2017) focus in California. Ravulaparthy et al. (2017) estimate a binary logit model for their propensity model, a linear regression model for frequency, and a utility function for allocation. Lugo & Srinivasan (2016) use data fusion followed by a linear regression model. Li et al. (2016) estimate a negative binomial regression model for trip choice and frequency, and linear regression to model average walking distance.

4.3.6 Miscellaneous Methods

Six of the papers we found use methods that do not fit into the categories above. They are nonetheless of interest for the research questions they are answering.

Two of these papers have study areas in California. Brozen et al. (2017) is the only paper we found that uses a qualitative method - long-form interviews - to identify challenges and opportunities based on interviews of modelers and representatives of various California MPOs. Moreover, Macias (2016) is the lone paper who relies exclusively on GIS. Focusing on the Expo

Line in Los Angeles Metro Rail System, the author compares three approaches for identifying pedestrian catchment areas to two traditional approaches.

In the greater Toronto and Hamilton area, Colley & Buliung (2016) calculate descriptive statistics to investigate the gender gap in school and work travel. They do not estimate any of the other models discussed in this review.

Moreover, three papers model facility demand using alternatives to the linear and negative binomial regressions discussed earlier. Gast et al. (2015) construct a Markovian queueing model to forecast the future availability of bicycles docked at stations of the Vélib bike-sharing system in Paris, France. Two other papers use Bayesian methods. In Vancouver, Canada, Osama et al. (2017) develop zone-level ridership models. They find that more connected, dense, flat, continuous, recreational, and off-street bike networks yield higher bicycle-kilometers-traveled (BKT). In Dublin, Ireland, Doorley et al. (2014) apply a Bayesian structural time series model to observations of cyclist traffic volumes in segregated bike lanes.

5. Active Transportation in the Orange County Transportation Analysis Model

5.1 Background on OCTAM

The Orange County Transportation Analysis Model (OCTAM) is a regional model that is based on the traditional four-step (i.e., trip generation, trip distribution, modal choice, and trip assignment) modeling methodology. OCTAM implements a multi-modal approach to analyze the following travel modes: local and express bus transit, urban rail, commuter rail, toll roads, carpools, truck traffic, as well as non-motorized transportation which includes pedestrian and bicycle trips. OCTAM accounts for land use types, household characteristics, state of the transportation infrastructure, and travel costs such as transit fares, parking costs, tolls, and automobile operating costs. OCTAM uses socioeconomic data to estimate trip generation and mode choice, as well as several sub-models to address complex travel behavior and multimodal transportation issues. Our focus here is on OCTAM's active transportation modeling tool.

5.2 Active Transportation Modeling Tool

To help meet statewide GHG reduction goals, OCTA contracted with Fehr & Peers to develop an Active Transportation (AT) Modeling Tool that allows for a more robust analysis of the costs and benefits of various active transportation improvement scenarios throughout the region. The AT Modeling tool is an add-in module to the OCTAM TransCAD software. It is designed to evaluate the effects on travel demand of interventions used to promote active transportation, such as land use changes, new sidewalks, roadway speed restrictions, and new bicycle lanes. Table 1 highlights the input variables used in the AT module.

5.3 Comparing OCTAM AT Module's Variables to Other Models

During the course of this project, OCTA representatives requested a comparison of the OCTAM Active Transportation Module's coefficients with the coefficients of other models. However, only one study – Marshall & Henao (2015) – has two variables (Intersection Density and Bus Stop Density) that are defined exactly as in the OCTAM AT Module. Unfortunately, that study's authors declined to share any of the coefficients for their multinomial logit model. In other studies, differences in modes or independent variables make such direct comparisons inappropriate. Tables 2 and 3 illustrate the infeasibility of such a comparison.

Table 1. Active Transportation Modeling Tool Input Variables

Variable	Description
TAZ	Traffic Analysis Zone
Place Type Group	SCAG Place Type Group of the Scenario Planning Zones within the TAZ.
worker	Number of workers as a proportion of total TAZ population.
kid	Number of children as a proportion of total TAZ population.
nw1824	Number of non-workers aged 18 to 24 as a proportion of the total TAZ.
nw6599	Number of non-workers over 64 as a proportion of the total TAZ population.
HHVEH	Number of vehicles per household.
HHSIZE	Average household size.
inc1	Proportion of households with an annual income under $35k.
inc2	Proportion of households with an annual income between $35k & $50k.
inc5	Proportion of households with an annual income between $100k & $150k.
inc6	Proportion of households with an annual income over $150k.
int_den	Intersection density (intersections per square mile).
mxd_den	MXD model density: sum of population & employment divided by area (mi^2).
mxd_div	MXD model diversity. 1 – ABS(empl. – 0.2 * pop.) / (empl. + 0.2 * pop.)
Dmxd_den	MXD model density (Destination).
Dmxd_div	MXD model diversity (Destination).
Dint_den	Intersection density (Destination).
O_25mD	Street density of roadways with speeds less than 25 mph (miles per acre).
O_35mD	Street density of roadways with speeds higher than 35 mph (miles per acre).
O_BLden1	We bikeways density (miles/acre). Class weights: I=3, II=2, III=1
D_25mD	Street density of roadways with speeds under 25 mph (Destination).
D_35mD	Street density of roadways with speeds over 35 mph (Destination).
D_BLden1	Weighted bikeways density (Destination).
O_stopD	Bus stop density at origin (per square mile).
D_stopD	Bus stop density at destination (per square mile).
O_hrPC	Parking cost.
D_hrPC	Parking cost (Destination).
Walk_Infrastructure	Level of pedestrian infrastructure (Low, Medium, or High).

Table 2. OCTAM AT Module Variables that Appear in Other Discrete Choice Models

	CA	Multinomial logit						Other	
Study number (see notes):	1	2	3	4	5	6	7	8	9
Modes									
Drive		X					X		X
Transit		X					X		X
Walk		X	X		X	X	X	X	X
Walk-to-Transit									
Bike	X	X	X	X			X		X
Input Variables from OCTAM AT Module									
Place Type Group									
Workers per Population						X			
Children Per Population		X				X			X
Non-Workers (Ages 18 to 24)									
Non-Workers (Ages 65 and Over)									
Vehicles Per Household	X					X		X	
Average Household Size		X				X		X	
Income	X			X			X		X
Intersection Density (Per Square Mile)							X		
MXD Density		X		X	X		X		X
MXD Diversity				X	X		X		X
Street Density (Two Variables)									
(Weighted) Bike Lane Density	X								
Bus Stop Density							X		
Parking Cost									
Pedestrian Infrastructure			X		X	X			

Notes. The studies above are: 1. Ravulaparthy *et al.* (2017); 2. Hasnine *et al.* (2017) [multinomial logit, nested logit, & cross-nested logit]; 3. Reardon *et al.* (2017); 4. Broach & Drill (2016); 5. Clifton *et al.* (2016a); 6. Clifton *et al.* (2016b); 7. Marshall & Henao (2015); 8. Habib *et al.* (2014) [ordered probit]; 9. Fatmi & Habib (2016) [random parameters logit].

Table 2 shows which variables from the OCTAM Active Transportation Module have analogues in nine other discrete choice studies found during our review. One California study uses a binomial logit model. Studies 2-7 primarily estimate multinomial logit models, and studies 8 and 9 consider other models.

The first complication that arises in comparing coefficients across studies is that of all the variables in Table 2, only Intersection Density and Bus Stop Density are defined in another study in the same way as in the OCTAM AT Module. That study – Marshall & Henao (2015) – estimates a multinomial logit discrete choice model. Unfortunately, the study does not provide the coefficient of its multinomial logit model and its focus is different (it was to map the proportion of income that Denver -area households spent on transportation.)

Another complication is that none of the studies in Table 2 model all five of the modes in the OCTAM AT Module. Only Hasnine *et al.* (2017), Marshall & Henao (2015), and Fatmi & Habib (2016) model four of these five modes: Drive, Transit, Walk, and Bike. Reardon *et al.* (2017) model walking and biking, but the remaining studies only consider either walking or biking. None of the 9 studies considers Walk-to-Transit separately.

In the nine studies referenced in Table 2, there are no analogues for the OCTAM AT Module's Place Type Group, Street Density, and Parking Cost variables. While other studies include variables related to specific land uses (e.g. retail, government, finance, and industrial employment in Clifton et al., 2016a), the Place Type Group is a fully developed and exhaustive categorization of land uses in OCTAM. (Note: The AT Module employs the Place Type Group variable to adjust an active transportation mode's utility value according to the level of walking infrastructure.)

The absence of an analogue to the Street Density variables is notable because in the OCTAM AT Module, these street densities correspond to two different street speeds: roadways with speeds under 25 mph, and roadways with speeds over 35 mph. This variable allows the OCTAM AT Module to model roadway speed reductions. In contrast, the other studies in Table 2are unable to model this strategy.

For other variables from the OCTAM AT Module, the nine comparison studies have analogues but define them differently, which hampers comparisons. For example, the OCTAM AT Module has three variables related to the number of workers: Workers per Population (the proportion of a TAZ's population who are workers), Non-Workers aged 18-24, and Non-Workers aged 65 and over. All three are continuous variables. In contrast, other studies take different approaches. For example, Clifton *et al.* (2016b) use dummy variables: 1 worker (yes/no) or 2 workers (yes/no). In addition, other models have dedicated age variables, whereas the OCTAM AT Module breaks its non-working population into age groups (18-24 and 65 & over). Some models, like Ravulaparthy *et al.* (2017), use a dummy variable to indicate a specific age group (in this case, people aged 44+) while other studies, like Fatmi & Habib (2016), use a continuous variable for age.

For income, the thresholds categories differ between studies. The OCTAM AT Module considers four categories: <$35k, $35k-$50k, $100k-$150k, and >$150k. In contrast, Broach & Dill (2017) use only one dummy variable for income - if an individual has a median income between $50k-$100k. Fatmi & Habib (2016) use three dummy variables for income less than $50k, income greater than $75k, and income greater than $150k.

Vehicles per Household is another variable treated differently by different studies. In the OCTAM AT Module, it is a continuous variable – HHVEH, the number of vehicles per household. In contrast, Clifton *et al.* (2016b) use dummy variables for owning no cars, 1 car, 2 cars, or 3+ cars. Such definitional differences make direct comparison difficult.

While there are no direct analogues for the OCTAM AT Module's MXD Density and MXD Diversity variables, the nine comparison studies in Table 2 use other means to incorporate employment and population data. For example, Hasnine *et al.* (2017) has an employment density variable, but it is not combined with population density. Fatmi & Habib (2016) create a land use index that includes both employment and population, but these variables are combined differently. Ultimately, the uniqueness of the MXD Density and Diversity variables makes any direct comparison of coefficients problematic.

Pedestrian infrastructure is also defined differently in the comparison studies of Table 2. The Walk Infrastructure variable in the OCTAM AT Module is qualitative and can take on three values: "Low", "Medium", or "High". In contrast, Clifton et *al.* (2016a-b) define a quantitative Pedestrian Index of the Environment (PIE) and Reardon *et al.* (2017) use the commercially available WalkScore™ in their multinomial logit model.

Although comparison with models in papers listed in Table 2 is not possible, Appendix B compiles the coefficient values of these models for completeness.

Table 3. Other Modes and Variables in Selected Discrete Choice Studies

Study	Other Modes	Other Variables
Ravulaparthy et al. (2017)		***Sociodemographic*****:** age, gender, education ***Physical*****:** average slope of tract ***Relation to alternative transport infrastructure:*** distance to nearest trail ***Alternative transport availability*****:** presence of bike share, transit availability in home tract
Hasnine et al. (2017)	Auto Passenger Park-and-Ride Kiss-and-Ride Bike-and-Ride	***Sociodemographic:*** age ***Generalized costs*****:** travel cost, distance, travel time ***Employment*****:** employment density ***Ownership of mode*****:** transit pass ownership, Presto card ownership, bike ownership ***Gender-destination combination*****:** Female Students commuting to Downtown Campus, Female Students commuting to Suburban Campus ***Pedestrian environment*****:** Area (sq. km) of 1000 m walk buffer ***Relation to alternative transport infrastructure***: Number of transit trips departing w/in 400m walking distance; Distance to nearest bus stop, rail stop, & subway stop ***Other*****:** Coefficient of the Expected Max Utility of Transit Nest, Coefficient of the Expected Max Utility of Active Transport Nest
Reardon et al. (2017)	By trip purpose: ●Walk to school ●Bike to school ●Walk to shop	***Generalized costs:*** distance ***Pedestrian environment:*** walk score at origin and destination

Study	Other Modes	Other Variables
	●Bike to shop ●Walk recreationally ●Bike recreationally	
Broach & Dill (2016)	Walking only, by trip purpose: ● Home-based Work ● Home-based shopping ● Home-based recreation ● Home-based other ● Non-home-based work ● Non-home-based work	***Sociodemographic***: age, education ***Employment***: jobs within 1 and 5 shortest path miles; proportion of jobs w/in 5 shortest path miles of CBD ***Biking Environment***: route quality index
Clifton et al. (2016a)		***Generalized costs:*** distance ***Employment***: retail, government, finance, and all other jobs; proportion of industrial jobs ***Population***: number of households ***Physical***: average slope of tract

Study	Other Modes	Other Variables
		Pedestrian environment: park available, pedestrian index of the environment (PIE), freeway present
Clifton et al. (2016b)		***Sociodemographic:*** age ***Origin-Destination related:*** trip end located beyond PIE extents, trip end located in Washington state ***Trip purposes*****:** home-based shopping, home-based recreation ***Pedestrian environment:*** pedestrian index of the environment (PIE), miles of freeways within 1/8 mile
Marshall & Henao (2015)		***Sociodemographic*****:** education score, ethnicity (White, Nonwhite, African-American, Hispanic, Asian, Native American) ***Employment*****:** ratio employees/population; employment density ***Population*****:** population density ***Income-related*****:** % of household income spent on commuting ***Dwelling-related*****:** year built for housing stock ***Network properties:*** link-node ratio *Relation to alt transport infrastructure*: **distance from light rail, park-and-ride, bus stop, Denver CBD, Denver Tech Center, downtown Boulder**
Habib et al. (2014)		***Sociodemographic:*** age, gender

Study	Other Modes	Other Variables
		Population: home zone population density ***Dwelling-related***: living in Townhouse ***Student status***: secondary school, post-secondary school ***Specific land uses***: general office, other occupation category
Fatmi & Habib (2016)	Mode transitions modeled as well: ● Car to transit ● Car to active transportation ● Transit to car ● Transit to active transportation ● Active Transportation to car ● Active transportation to transit	***Sociodemographic***: age, gender, education ***Household type***: single-worker, full-time Dual-worker ***Income-related***: increase/decrease in household income over previous year ***Ownership of mode***: no car ownership, addition of car (same year) ***Dwelling-related***: moved from rented to owned or reverse; increase / decrease in number of. Bedrooms; % single-family detached ***Life transition events***: birth of a child (1 yr. lead), new household formation, addition of job (1 & 2 year lead); lost job (1 & 2 year lead), lost job (2 year lead) ***Trip purpose-related***: moved closer to work, Moved closer to school, Moved closer to CBD, Moved farther from CBD ***Land Use-Related***: land Use Mix Index ***Relation to alt transport infrastructure***: distance to nearest transit station, to nearest park, to CBD; moved closer to/farther from transit station; moved closer to park area, % transit trips, % active transportation trips

6. Conclusions and Suggestions for Next Steps

In this report, we reviewed a selection of recent academic papers to understand the state-of-the-art to model active transportation and we started exploring the capabilities of the OCTAM Active Transportation (AT) Module. Our literature search returned 34 papers published between 2012 and 2017. We analyzed these papers based on geography and on methodology, before attempting to compare the variables in the OCTAM AT Module with those in similar models.

In terms of geography, the search returned three papers whose study areas are in California. Of the studies above, only one (Ravulaparthy *et al.*, 2017) attempt to model mode choice – specifically, using a binary logit choice model. Elsewhere in the US, Portland, OR and Salt Lake City, UT are the two cities with the most relevant case studies. Internationally, Toronto, Canada, has attracted a lot of research attention recently with several case studies.

In terms of methodology, our search returned five studies which either used four-step models or analyzed data from four step models. Our search also returned six studies that rely on multinomial logit models. Of these, two Portland (OR) area studies (Clifton *et al.*, 2016a-b) estimated multinomial logit models using data from four-step models. The models in these papers – which are similar, but not identical – incorporate explanatory variables that relate to land use mix and pedestrian facilities. However, they do not include variables relating to bicycle lanes or roadway speed restrictions.

The multinomial logit models mentioned in Section IV cover three of the four strategies available to OCTA: land use change, new sidewalks, and new bicycle lanes. However, variables relating to roadway speed (and, hence, the possibility of modeling roadway speed restrictions) are notably absent from the papers we found during our literature search. While our review focuses on four-step models and multinomial logit choice models, the largest other group of active transportation papers consisted of studies on modeling counts on pedestrian and bicycle facilities. These papers use primarily negative binomial regression or linear regression.

We attempted to compare the coefficients of the OCTAM AT Module with those in other discrete mode choice studies (in California and elsewhere). Unfortunately, such direct comparisons are infeasible because the structure of published models (and therefore the interpretation of their variables) or the definition of variables of interest (continuous, binary, or corresponding to an interval) differ too much from the structure of the OCTAM AT Module or from its explanatory variables to allow comparison. Only one study – Marshall & Henao (2015) – has two variables (Intersection Density and Bus Stop Density) that are defined exactly as in the OCTAM AT Module. Unfortunately, that study's authors did not share the coefficients of their multinomial logit model.

The specification of the OCTAM AT seems reasonably in light of the recent studies reviewed in this document. One limitation is that we started working with the OCTAM AT module relatively late during this phase of the study, so we did not have time to evaluate its performance on real case studies or to compare its predictions with observed behavior. In light of our literature review and of general considerations about people’s mode choices, however, we make the following observations/suggestions:

1. First, we note that OCTAM AT does not include variables that could impact people’s decision to leave their vehicles at home in favor of transit. These variables relate to economic conditions (such as gasoline prices, the median wage and the unemployment rate), perceptions (such as safety both from traffic and from crime), and the quality of both the biking network (e.g., see Broach & Dill, 2017), and walking routes (including pedestrian signals at major crossings) (Broach and Dill, 2016);
2. Second, a number of conditions need to be jointly met for people to walk or bike (e.g., existence of continuous sidewalks or a dense enough network of bike lanes, safety from both traffic and crime); in isolation, these conditions would not lead to people walking. One way to represent this dependence in statistical models is to use interaction terms; and
3. Third, OCTAM AT does not capture residential self-selection, which could be important here as people who do not plan to walk/bike self-select into car-oriented neighborhoods. One convenient tool to tackle this issue is generalized structural equations modeling (GSEM) (Kline, 2015). A well-specified GSEM model could incorporate a multinomial or a count model and include latent factors characterizing people’s attitudes based on additional information while controlling for residential self-selection.

These ideas could be starting points for a more in-depth conversation with OCTA staff for the next phase of this project.

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Appendix A: Paper Summary Matrix

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
2017				
Broach & Dill (2017)	Predict the impact of various network and land-use changes on bicycling using readily available data	Linear regression	Portland region, OR (4 counties) • 1,200 to 8,000 people • Census Tracts from 5-year (2010-2014) American Community Survey (ACS). • Employment destination data from Census Longitudinal Employer-Household Dynamics database.	Network quality: • matters not only in decisions of where to bike, but also whether to bike. • has ~3 times the expected effect on bike commuting than job access alone.
Brozen *et al.* (2017)	Interview MPO representatives to identify improvements to incorporate into the next generation of activity-based regional travel demand models.	In-depth interviews.	Four Metropolitan Planning Organizations (MPOs) in California. • Two staff members for each MPO. • Seven of the eight interviews conducted in-person. • Each interview approx. 45 min.	• Household travel surveys underrepresent walking. • MPOs have difficulty locating pedestrian network improvements without an inventory of walking network & the quality of pedestrian infrastructure. • Regional travel demand models not well suited to understand the factors that induce or improve walking. • Limited data on geography of walk trips inhibits model calibration and identification of walking volumes.
Currans (2017)	Identify problematic gaps in the state-of-the-art trip generation methods.	Literature Review.	Google Scholar and library searches.	Current literature shows... • understanding of the influences of the built environment on vehicular trips, but not necessarily on multimodal trips. • little understanding about the influences of trip-maker socio-demographics on behavior.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Garikapati *et al.* (2017)	Calculate household travel energy consumption at the TAZ level using information readily available from a standard four-step travel demand model system.	Trip distribution algorithms.	Greater Atlanta metro region. Atlanta Regional Commission (ARC) model • 2,024 TAZs. •5,231,307 people; 1,835,786 households. • Total employment 2,385,720. • National Household Travel Surveyfor socio-economic data & vehicle fleet mix.	Travel energy footprint strongly correlated to density of the built environment.
Hasnine *et al.* (2017)	Investigate the mode choice behavior of post-secondary students commuting to school in the city of Toronto.	Multinomial logit, nested logit and cross-nested logit models	Four universities in Toronto: a) Ontario College of Art and Design; b) Ryerson University; c) York University; and d) The University of Toronto. 15226 complete responses in Fall 2015.	• Female students who travel towards downtown are more transit and active mode oriented than those who travel away from downtown. • Mobility tool ownership (i.e., transit pass, car and bike ownership) and age groups influence students' mode choice behavior.
Ingvardson *et al.* (2017)	Model habitual travel behavior and represent habit formation.	Structural Equation Model	Greater Copenhagen area. 1481 complete responses.	• Higher bicycle satisfaction relates positively to cycling self-concepts and negatively to car self-concepts. • Greater car use satisfaction increases with car self-concepts and transit use difficulties, and decreases with difficulties in car use and better cycling self-efficacy. • Higher transit satisfaction relates to experiencing difficulties with other modes.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Jamali & Wang (2017)	1) Synthesize previous studies and offer best practices for estimating pedestrian exposure in rural and small urban areas; 2) Estimate a household-level pedestrian exposure measure for rural and small urban settings.	Literature review for first goal. Negative binomial regression model for the second goal.	US National Household Travel Survey (NHTS) data, focusing on rural and small urban areas. 11,692 home-based walk-only trips in nine states (Montana, Oregon, Wyoming, California, Arizona, Texas, South Dakota, New York, and Florida)	• Four general types of exposure metrics: area-based measures, point-based measures, segment-based measures, and behavioral attributes of walk trips. • The regression model accounted for household characteristics, regional factors, and block-group-level attributes (e.g., population density and school density).
Lu *et al.* (2017)	Study comprehensive bicycle and pedestrian traffic monitoring campaign in a small, rural college town.	Negative Binomial Regression (NM)	45,456 hours of bicycle and pedestrian traffic counts at 101 locations 210 in Blacksburg, VA	Strong correlation between validation counts and automated counts. Correction equations varied by the type of counter.
Osama *et al.* (2017)	Evaluate the impacts of network indicators, land use, and road facility on bike kilometers traveled (BKT) by developing zone-level ridership models.	Bayesian Analysis	Land use and road facility data for 134 TAZs in Vancouver, Canada. Bike counts between 2005-2011.	Results suggest that more connected, dense, flat, continuous, recreational, and off-street bike networks yielded higher BKT.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Ravulaparthy *et al.* (2017)	Create a toolbox of statistical models to determine propensity and frequency of recreational travel, and to allocate recreational trips to individual bicycle facilities.	• Binary logit for Propensity Model. • Linear regression for Frequency model. • Utility function for Allocation model.	Los Angeles county, CA. • Propensity and Frequency models: 2009 NHTS • Allocation model: 2008 National Survey of Bicyclist and Pedestrian Attitudes and Behavior • Southern California Association of Governments synthetic population for 2008 base year. • Scenarios analyzed: 2015 No Build, 2015 "Un-Build" (i.e. remove all bike treatments in the 2015 No Build scenario), and 2015 Bike Share.	• Demand generation: 2015 Un-Build scenario has fewer riders and BMT compared to others. • Demand allocation: Both the incidence of treated bicycle facilities and the presence of a bike share program increase bicycling.
Reardon *et al.* (2017)	Examine the Network Utility approach developed by Boston's Metropolitan Area Planning Council which seeks to produce roadway segment-level estimates of active transportation network utility	Multinomial Logit	Household and individual-level responses from the 2011- 2012 Massachusetts Travel Survey (MTS)	Network Utility Scores can be combined with additional information to identify infrastructure gaps and improvement priorities
Steinmetz-Wood *et al.* (2017)	Examine the influence of the geographical size and scale of census units on the relationship between land-use mix and route choice to work using active transportation.	Cross-classified multilevel logistic regression.	2010-11 Massachusetts Travel Survey. Sample limited to adults aged 18 to 65. Final sample size 14,773 people.	• Area correction increases the size of the odds ratio of using active transportation at all scales analyzed. • Size and significance of the land-use mix odds ratio varied with geographical scale for both original and area corrected land-use mix. • Significant positive relationships in using active transportation for area corrected residential and workplace tract land-use mix.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Zimmermann *et al.* (2017)	Develop a link-based route choice model that 1) overcomes variability in estimation results and 2) incorporates non-link additive attributes (e.g. slope).	Recursive Logit and Nested Recursive Logit	648 GPS-based path observations in Eugene, OR. Matched to route network of 16,352 nodes and 42,384 links.	Results demonstrate that cyclists are sensitive to distance, traffic volume, slope, crossings, and the presence of bike facilities.
2016				
Bernardin & Chen (2016)	Develop models to improve the accuracy and response properties of non-home-based (NHB) trips in trip-based models.	Linear regression models	Salt Lake City, UT. Wasatch Front Regional Council (WFRC) model: • 2,200 TAZ • 6 trip purposes and 6 modes • Auto ownership, mode choice, & feedback • 1.7 million population	• Reasonable responses to hypothetical new residential growth • Plausible mode shifts in response to hypothetical enhanced transit service. • Better replication of observed NHB trip rates, mode shares and OD patterns with less calibration.
Broach & Dill (2016)	Test the effect of specific travel environment features on mode choice compared with route choice.	Multinomial logit	14,000 cycling trips taken in the city of Portland, OR from 2010 to 2013.	For cycling, excess distance, upslope, motor vehicle traffic, and specific bicycle infrastructure all have significant and similar effects on route and mode choice decisions.
Clifton *et al.* (2016a)	First study to analyze and model the destination choice behaviors of pedestrians within an entire region	Multinomial Logit	4500 walk trips from 2011 household travel survey in the Portland, OR region.	Distance was a significant deterrent to pedestrian destination choice, and people in carless or childless households were less sensitive to distance for some purposes.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Clifton *et al.* (2016b)	Represent pedestrian activity more effectively within four-step travel demand models	Multinomial Logit	4094 walk trips from 2011 household travel survey in the Portland, OR region.	Pedestrian demand model can forecast for an entire metropolitan region with spatial acuity and sensitivity to small-scale variations in the built environment. Improved travel model sensitivity to pedestrian-relevant factors. Results are more responsive to socio-economic changes and policy interventions.
Colley & Buliung (2016)	Investigate how the gender gap in school and work travel changes as individuals age. Investigate how household characteristics and factors such as distance and licensing associate with gender differences in commuter mode share.	Descriptive statistics.	Greater Toronto and Hamilton area, Canada's Transportation Tomorrow Survey (TTS).	• Female children are driven to school more frequently than males. • Factors associated with the largest differences in driving between full time-employed women and men: having one vehicle per household, more than six household members, and living and working in Toronto. • The gender gap in active transportation, public transit, and automobile use appears to be lower today than in the mid-1980s.
Davis & Leven (2016)	Estimate if land use and other regionally applied policies (intended to make better use of the transit system or postpone the need for expansion) would be sufficient to handle the projected forecast growth in the Washington, DC metro region.	Travel Demand Model coupled with the WMATA Postprocess or Model.	Washington, DC metro region. • 2040 baseline population and employment forecasts from the Metropolitan Washington Council of Governments (MWCOG) • Base travel model: Transportation Planning Board (TPB) Version 2.3.52. • Postprocessor model: Regional Transit System Plan (RTSP) Two scenarios with 3 iterations each (six total).	• Locating people and jobs in mixed-use areas with good transit increases transit ridership and decreases VMT • Regional approach to development provides greater impacts across a variety of measures. • Increasing the mix of uses in activity centers increases reverse commutes. • Small changes do not significantly shift outcomes if land use unchanged. • Disincentives to driving positively affects a number of measures, but may not be necessary to increase transit ridership.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Fagnant & Kockelman (2016)	Develop a direct-demand model for estimating peak-period cyclist counts based on trip generation and attraction factors (such as site-based population and employment densities)	Poisson regression and Negative Binomial	Seattle metropolitan area cyclist count data from 251 locations. Average Annual Daily Traffic (AADT) volumes (for automotive traffic) had to be obtained from numerous sources, covering cities across the State of Washington.	Wider bike lanes and curb lanes, along with lower traffic volumes, create favorable conditions for higher numbers of cyclists. The two preferred models developed here indicate either the use of curb lane width or bike lane width or automotive traffic volume be used.
Fatmi & Habib (2016)	Develop a dynamic model for individuals' commute mode choice over their lifetime by using retrospective survey data.	Panel-based random-parameters logit model	Halifax, Canada. Retrospective Household Mobility and Travel Survey (HMTS), Sep 2012 to Apr 2013. Sample size of 288 households.	• High-income individuals tend to be car loyal. • Probability of transit loyalty increases with no car ownership over the lifetime and the addition of a job. • Individuals with no children and residing in an area with high walk and bike usage more loyal to active transportation. • A decrease in household income and tenure transition from owned to rental are likely to trigger a transition from car to transit. • Children and the addition of a car increase the transition propensity from transit to car.
Hankey & Lindsey (2016)	Build on previous exploratory facility-demand models of pedestrian and bicycle traffic in Minneapolis. Employs a new, larger data set of peak period (4 to 6 p.m.), volunteer based counts (n = 954).	Stepwise linear regression	Peak period (4 to 6 p.m.) counts of pedestrian and bicycle traffic in Minneapolis, Minnesota. Count database (n=5954 observations; 471 locations).	Results suggest that reduced-form models perform nearly as well as fully specified models and are easier to apply and interpret.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Li *et al.* (2016)	Explore the impact of different land use types on pedestrian trip generation, frequency and distance.	• Zero-Inflated Negative Binomial Regression for the trip choice and frequency models. • Linear regression model for the average walking distance model.	Salt Lake City-West Valley and Ogden-Layton urbanized areas (Utah). • Household Characteristics: 2012 Utah Household Travel Survey (5,071 responses). • Street data: UT Automated Geographic Reference Center. Bike lanes: County GIS depts. Parcel data: County Assessors. • Employment: UT Dept. of Workforce Services. • Natural Environment: UT Automated Geographic Reference Center.	Factors that positively influence the propensity and frequency of walk trips: • size of household, • land use mix, • presence of non-residential destinations, • street connectivity
Loong & El-Geneidy (2016)	Investigate the amount of additional time commuters allocate to account for travel time unreliability.	Log-linear regression models.	2013 McGill Commuter Survey (Montreal, Quebec). 5,599 complete records (32% response rate).	• Perception that the street network is unreliable (for either buses or cars). • Drivers allocate the most extra time for their commute. • Users of other modes (transit, bicycle, and pedestrian) budget ~29% to 66% less than drivers. • Bus commuters add 14% more buffer time per bus taken. • Train users budget 11% less time for every commuter train taken.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Lugo & Srinivasan (2016)	Demonstrate the feasibility of using data fusion in large-scale travel and health surveys. Then model the relationship between health and multi-modal (walking, biking, transit, and vehicle usage) long-term (weekly/monthly/ yearly) travel choices.	Data fusion and linear regression model.	Data Fusion compares "Receiver" dataset with records of a "Donor" dataset to identify the record from the "Donor" that best matches each record in the "Receiver" on a set of pre-defined attributes. • Donor dataset: 2006-2008 American Time Use Survey Eating and Health Module (ATUS-EH). • Receiver dataset: 2009 National Household Travel Survey (NHTS). • 36,000 donor records potentially matched with 11,362 receivers.	• Biking no statistically significant impact on Body Mass Index (BMI) or Self-Assessed Physical Health Score (SAPHS). • Pedestrians have a lower BMI and feel better, but those who walk more than 6 trips/week are in poorer health than those who walk 4-5 trips. • Transit users (2-3 trips/month) have a lower BMI than others. • Those who drive between 5,000-15,000 miles a year have lower BMI than those who drive >15,000 miles.
Macias (2016)	Compare 3 new approaches for identifying pedestrian catchment areas (network grade, pedestrian speed, and pedestrian energy methods) to two traditional approaches (Euclidean distance and network distance methods).	Spatial analysis in GIS and single-factor ANOVA to compare the five approaches.	Expo Line in Los Angeles. 8.8-mi (14.1-km) light rail corridor with 12 stations.	• The study's methods generate catchment areas of significantly different sizes. • Euclidian approach (Method 1) can mislead planners into investing finite resources in streets not accessible by transit.
2015				
Gast *et al.* (2015)	Improve forecasts about the future availability of bicycles in stations of a bike-sharing system (BSS)	Markovian Model	Data from the *Vélib* system in Paris collected between 1 October 2013 and 31 December 2014.	Probabilistic forecasts may broaden the scope of the applicability of predictive models. They provide more direct user-centric quantities useful for journey planning, such as the probability of finding a bike at the origin station.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Idris *et al.* (2015)	Investigate the over-prediction of public transit ridership by traditional mode choice models estimated using revealed preference data	Four models: • RP (Revealed Preference) mode choice model w/ latent variable. • SP (Stated Preference) mode switching model. • Joint RP/SP mode switching model. • Hybrid mode switching model w/ latent variable.	Census Metropolitan Area (CMA) of Toronto, Canada between April and May 2012. Original dataset: 1211 observations. Subset used: 774 observations representing individuals who reported ''Car Driver'' as their primary mode for daily work commute.	• Models with latent habit outperformed the traditional mode choice model. However, mode shift models without latent habit outperformed mode shift models that had the latent habit variable. • Poorest forecasting: traditional RP data-based mode choice model. • Best forecasting: the SP data-based and the joint RP/SP mode shift models. • Traditional RP data-based mode choice model has tendency to over-predict transit ridership.
Marshall & Henao (2015)	Explore resiliency, vulnerability, and transportation affordability issues with the questions on driving cost, distance to downtown or employment, transit infrastructure, and current travel behavior.	Multinomial logit	Denver, CO metro area. Denver Regional Council of Governments (DRCOG) activity-based travel model. Final sample included 1,154,673 home-to-work tours, comprising 654,762 home TAZ to work TAZ combinations. Supplemented with data from the 2008 American Community Survey (ACS) (2,032 block groups).	• Higher resilience found in locations with proximity to high levels of employment, with more compact and connected street networks, and with better transit infrastructure. • Being a public transit user not as important to resilience as living near better transit infrastructure. • Transportation choice creates network redundancy, facilitates adaptability under extreme conditions.

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
Mjahed *et al.* (2015)	Explore the role of childhood experience on the underlying motives and determinants of walking behavior.	Structural Equation Model.	Online attitudinal survey distributed July 2014 via social media and e-mail. International respondents. 207 completed responses (response rate of 81.5%).	• Results support the existence of a relationship between travel behavior during childhood and walking behavior during adulthood. • Determinants of walking differ based on region of residence.
2014				
Doorley *et al.* (2014)	Test the forecasting accuracy of structural time series models applied to continuous observations of cyclist traffic volumes	Basic Structural Model (BSM)	Hourly cyclist volumes recorded in both directions for segregated bicycle lane in Dublin, Ireland between Monday, October 3rd, 2011, 00:00 and Thursday, August 30th, 2012, 23:00	Models can produce accurate peak period forecasts of cyclist traffic volumes at both 1 hour and fifteen-minute resolution and that the percentage errors are lower for hourly forecasts
Habib *et al.* (2014)	Investigates walking-trip generation for commuting	Ordered probit model	Household travel survey data collected in the Greater Toronto and Hamilton Area (GTHA) in 1996, 2001 and 2006	Zonal-level average auto ownership is more influential than household auto ownership.
2013				
Kim & Susilo (2013)	Construct various pedestrian trip generation models for the Baltimore region using National Household Travel Survey (NHTS) data	Negative Binomial Regression (NM) Poisson regression	National Household Travel Survey (NHTS) 2001 data for the Baltimore (USA) region MD Property View 2001 and MD Transit View 2001 (both published and managed by Maryland Department of Planning, MDP) were used to generate more detailed land-use variables.	PRM gives better model improvements between base model and estimated model. PRM can be a better modeling technique than NBRM in practice despite the theoretical advantages of NBRM for dealing with over-dispersed data

Author(s) (Date)	Research Question	Method(s)	Dataset	Key Findings
2012				
Hankey *et al.* (2012)	Develop models to estimate non-motorized traffic for streets where counts are unavailable or to estimate changes in non-motorized traffic associated with other changes in the built environment	Negative binomial model	Cyclists and pedestrians counts between 2007 and 2010 at 259 locations in the city of Minneapolis, MN	Bicycle traffic volumes in Minneapolis, MN are significantly increasing over time1 or 2 hr. bicycle and pedestrian counts can predict reasonable estimates of "daily' (12 hr.) counts.

Appendix B: Coefficients of the OCTAM AT and Table 2 Models

Appendix B contains the coefficients of the discrete choice models used in the OCTAM AT Module and the models in of this report. There are significant differences between the OCTA Active Transportation Module and the models found during our review in terms of the modes covered and the independent variables chosen. Consequently, we believe that in most cases, comparing coefficients between these models is unreasonable. Nonetheless, these coefficients are provided here for information.

OCTAM Active Transportation Module

These coefficients are reproduced here for comparison.

Variables	Constant	worker	Kid	nw1624	nw6599	HHVEH	HHSIZE
Transit	-5.150	-0.322	1.345	1.523	-0.281	-1.018	0.188
Walk	-2.250	-0.542	0.454	0.478	-0.149	-0.560	0.138
Walk-Transit	-4.150	0.000	-0.433	1.277	-0.496	-1.344	0.238
Bike	-3.750	0.000	0.541	1.059	-0.456	-0.486	0.075

Variables	inc1	inc2	inc5	inc6	int_den	mxd_den
Transit	0.873	0.305	0.000	0.000	0.000	0.000
Walk	0.409	0.000	-0.126	0.136	0.001	0.000
Walk-Transit	0.800	0.259	-0.453	0.000	0.001	0.000
Bike	0.000	0.000	0.000	0.000	0.002	0.000

Variables	Dmxd_den	Dmxd_div	Dint_den	O_25mD	O_35mD	O_BLden1
Transit	0.000	0.000	0.000	-11.593	0.000	
Walk	0.000	0.225	0.001	3.429	-7.147	
Walk-Transit				0.000	0.000	
Bike	0.000	0.000	0.001	7.307	-8.018	6.113

Variables	D_25mD	D_35mD	D_BLden1	O_stopD	D_stopD	O_hrPC	D_hrPC
Transit	-5.769	14.144		0.003	0.000	0.000	0.057
Walk	6.923	-8.842				0.000	0.000
Walk-Transit				0.001		0.024	
Bike	9.893	-8.732	5.333			0.000	0.000

Ravulaparthy *et al.* (2017)

A binary logit discrete choice model for the propensity to travel by bicycle.

Variables	Constant	Female	Age (44+)	Educ.: MS/MA+	Educ.: BS/BA	Educ.: Vocational/ AA	Educ.: High School/ GED	Education: less than HS
Bike	-1.17	-1.04	-0.044	0.707	0.677	0.544	0.414	0.00

Variables	# vehicles in HH	Density Class 1 facilities	Density Class 2 facilities	Density Class 3 facilities	Avg slope home tract	Distance to nearest trail	Transit availability in home tract	Presence of bike-share
Bike	-0.629	0.2	0.148	0.024	-7.79	-0.075	0.035	0.06

Hasnine *et al.* (2017)

This study presents three different discrete choice models (multinomial, nested, and cross-nested logit) for eight separate modes: driving, riding a car as a passenger, using transit, park & ride, kiss & ride, bike & ride, walking, and biking. Blank cells in these tables indicate that the coefficient is not specified for a specific variable and mode for that model. However, the corresponding value in one of the other two models could be nonzero.

Multinomial Logit

Variables	Const.	Travel Cost	Distance (km)	Travel Time	No. of household per # of members	Transit Pass Ownership	Presto Card Ownership	Bike Ownership
Auto Drive	0.000	-0.233		-0.001	3.744			
Auto Pass.	0.087	-0.233		-0.001				
Transit	1.770	-0.233		-0.001		1.649	0.808	
Park & Ride	-2.583	-0.233	-5.443	-0.001	3.744	1.649	0.808	
Kiss & Ride	-0.104	-0.233	-5.443	-0.001		1.649	0.808	
Bike & Ride	-1.399	-0.233		-0.001		1.649	0.808	
Walk	6.185	-0.233	-1.820	-0.001				
Bike	2.172	-0.233	-0.546	-0.001				1.469

Variables	Female Students Commuting Downtown	Female Students Commuting Suburban	Age 18-22	Age 22-25	Dependent children / # household members	Area (km^2) of 1000m walk buffer	No. transit trips departing w/in 400m walk dist.
Auto Drive					0.806		
Auto Pass.	0.355		0.721	-0.440			
Transit	0.068		0.315	-0.133			0.003
Park & Ride	0.654		-0.103	0.112			
Kiss & Ride	0.349		0.163	-0.549			
Bike & Ride	-0.617		-1.622	-0.508			
Walk	-0.374		0.165	0.469		0.048	
Bike	-0.382		0.058	0.669	-1.355		

Variables	Distance (km) to nearest bus stop	Distance to nearest rail stop	Distance to nearest subway stop	Employment Density	Coeff. Exp. Max. Utility of Transit Nest
Auto Drive				-0.037	
Auto Passenger				-0.043	
Transit	-0.067	-0.045	-0.032	-0.020	
Park & Ride				-0.020	
Kiss & Ride				-0.022	
Bike & Ride				-0.058	
Walk					
Bike					

Nested Logit

Variables	Cons.	Travel Cost	Distance (km)	Travel Time	No. of HH per no. of members	Transit Pass Ownership	Presto Card Ownership	Bike Ownership
Auto Drive	0.000	-0.228		0.000	6.927			
Auto Passenger	3.042	-0.228		0.000				
Transit	4.999	-0.228		0.000		2.213	0.912	
Park & Ride	-1.083	-0.228	-3.892	0.000	6.927	2.213	0.912	
Kiss & Ride	3.273	-0.228	-3.892	0.000		2.213	0.912	
Bike & Ride	2.047	-0.228		0.000		2.213	0.912	
Walk	10.985	-0.228	-2.108	0.000				
Bike	7.844	-0.228	-0.622	0.000				

Variables	Female Students Commuting Downtown	Female Students Commuting Suburban	Age 18-22	Age 22-25	Dependent children/ # household members	Area (km^2) of 1000m walk buffer	No. transit trips departing w/in 400m walk dist
Auto Drive					2.039		
Auto Passenger	-0.508		0.211	-0.615			
Transit	1.112	-0.590	0.244	-0.305			0.004
Park & Ride	1.987		-0.070				
Kiss & Ride	1.627		0.170	-0.480			
Bike & Ride	0.027		-1.498	-0.743			
Walk	0.757	-2.433	0.316	0.293			
Bike	0.823	-2.666	0.301	0.494	-1.683		

Variables	Distance to nearest bus stop (km)	Distance to nearest rail stop	Distance to nearest subway stop	Employment Density	Coeff. Exp. Max. Utility of Transit Nest
Auto Drive					0.810
Auto Passenger					0.810
Transit					0.810
Park & Ride					0.810
Kiss & Ride					0.810
Bike & Ride					0.810
Walk					0.810
Bike					0.810

Cross-Nested Logit

Variables	Cons.	Travel Cost	Distance (km)	Travel Time	# of HH / # members	Transit Pass Ownership	Presto Card Ownership	Bike Ownership
Auto Drive	0.000	-0.258		-0.010	4.128			
Auto Passenger	0.816	-0.258		-0.010				
Transit	2.626	-0.258		-0.010		2.071	1.034	
Park & Ride	-2.517	-0.258	-3.799	-0.010	4.128	2.071	1.034	
Kiss & Ride	-0.345	-0.258	-3.799	-0.010		2.071	1.034	
Bike & Ride	-0.791	-0.258		-0.010		2.071	1.034	
Walk	9.274	-0.258	-1.831	-0.010				
Bike	5.580	-0.258	-0.642	-0.010				1.248

Variables	Female Students Commuting Downtown	Female Students Commuting Suburban	Age 18-22	Age 22-25	Dependent children per no. household members	Area (km2) of 1000m walk buffer	No. transit trips departing w/in 400m walk dist
Auto Drive					0.603		
Auto Passenger	0.212		0.386	-0.548			
Transit	0.160		0.353	-0.381			0.004
Park & Ride	0.407		-0.069	-0.117			
Kiss & Ride	0.664		0.342	-0.772			
Bike & Ride	-0.952		-2.068	-1.292			
Walk	-0.199		0.127	0.175			
Bike	-0.226		0.072	0.497	-1.419		

Variables	Distance (km) to nearest bus stop	Distance to nearest rail stop	Distance to nearest subway stop	Employment Density	Coeff. Exp. Max. Utility of Transit Nest	Coeff. Exp. Max Utility of Active Transport Nest
Auto Drive				0.019		0.893
Auto Passenger				0.011		0.893
Transit	-0.412	-0.041	-0.030	0.024		0.893
Park & Ride				0.030		0.893
Kiss & Ride				0.028		0.893
Bike & Ride				-0.233		0.893
Walk						0.893
Bike						0.893

Reardon *et al.* (2017)

A multinomial logit discrete model for two modes (walking and biking) and three trip purposes (school, shopping, recreation)

Variables	Constant	Distance (Nat. Log)	Walk Score @ Origin	Walk Score @ Destination
Walking to school	-6.1047	-1.2565	0.0327	0.0255
Biking to school	-8.83973	-0.3864	0.0436	0.0256
Walking to Shop	-6.9397	-1.1514	0.0345	0.0311
Biking to shopping	-6.6096	-0.4451	0.0185	0.0234
Walking recreationally	-3.6973	-1.4086	0.0309	N/A
Biking recreationally	-3.5565	-0.8033	0.0198	N/A

Broach & Drill (2016)

A multinomial discrete choice model for one mode: bicycle. The authors created three models, of which Model 3 became the final model.

Variable	Const.	Jobs w/in 1 shortest path mi.	Jobs w/in 5 shortest path mi.	Route Quality Index	Proportion of jobs w/in 5 shortest path miles of CBD	% 25 & older w/ Bachelor's	% Age 15-34	Median income $50k-$100k
Biking	-8.1	-0.08	0.1	3.67	1.36	0.004	0.011	0.04

Clifton *et al.* (2016a)

A multinomial discrete choice model for one mode, and six trip purposes.

Variables	Distance	Retail Jobs	Gov't Jobs	Finance Jobs	All Other Jobs	No. House-holds	Pedestrian Index of the Environment
Walking (home-based work)	-1.35	2	2	2	0		0.30
Walking (home-based shopping)	-2.26	5.5	0	0	0		-0.01
Walking (home-based recreation)	-1.75	6.5	17.1	0	0	-2.00	0.01
Walking (Home-based other)	-1.94	3.8	3.8	0	0	0.12	0.03
Walking (Non-home-based work)	-1.42	5.5	0	2.5	0		0.02
Walking (Non-home based non-work)	-1.45	5.5	3.4	0	0		0.02

Variables	Slope (degrees)	Freeway Present	Proportion of Industrial Jobs
Walking (Home-Based Work)	-0.12	-0.30	-0.99
Walking (Home-Based Shopping)	-0.20	-1.02	-1.74
Walking (Home-Based Recreation)	-0.05	-0.17	-0.09
Walking (Home-Based Other)	-0.43	0.10	-0.40
Walking (Non-Home-Based Work)	-0.16	-0.14	-1.65
Walking (Non-Home Based Non-Work)	-0.06	0.26	-0.24

Clifton *et al.* (2016b)

A multinomial discrete choice model for one mode (walking). Trip purposes (Home-Based Shopping, Home-Based Recreation, and Home-Based School) are incorporated as variables.

Variables	Const.	House-hold Size	Age (56-65)	1 Worker in House-hold	2 Workers in House-hold	1 Child in Household	2 Children in Household	3+ Children in Household
Walking	-4.377	0.191	-0.242	0.208	0.301	0.295	0.455	0.479

Variables	0 autos owned by household	2 autos owned by household	3+ autos owned by household	Pedestrian Index of the Environment (PIE)	Trip end located beyond PIE Extents	Miles of Freeway w/in 1/8 mi
Walking	1.089	-0.463	-0.690	0.043	0.530	-1.093

Variables	Trip end located in Washington state	Home-Based Shopping Purpose	Home-Based Recreation Purpose	Home-Based School Purpose
Walking	0.792	-0.145	0.288	0.444

Marshall & Henao (2015)

This paper estimate a multinomial logit model for three modes (transit, walking, and biking). Unfortunately, it does not reveal the coefficients in its model.

Habib *et al.* (2014)

An ordered probit model that includes only one mode (Walking). Models were calculated for three separate years: 1996, 2001, and 2006. Only the latest model (2006) is shown below. Since the model is a probit model, the paper itself also includes a covariate matrix.

Variables	Constant	Home zone pop density	No car	Own 1+ cars	Zonal Avg household auto ownership	Dwelling = townhouse	Household size
Walking	-0.91	0.12	0.39	-0.22	-0.25	0	0.04

Variables	Age (25-35)	Age (35-45)	Female	Secondary School Student	Post secondary school	Occupation category: Gen Office	Occupation Category: Others
Walking	-0.09	-0.1	0.02	1.26	0.35	0.02	0.04

Fatmi & Habib (2016)

This study estimates discrete mode loyalty models rather than discrete mode choice. It estimates both a multinomial logit model and a random parameters logit model. While the models include three modes (Car, Transit, Active Transportation), the paper models both loyalty to these modes (3 models) and transitions between these modes (6 models).

Not all variables are used in all models. Blank cells in these tables indicate that the coefficient is not specified for that specific variable for that mode loyalty or transition. The original paper's tables only list coefficients for those variables which exist for that specific mode loyalty model, which facilitates the comparison of the multinomial logit model to Fatmi & Habib's preferred random parameters logit model.

Multinomial Logit

Variables	Const.	Male	Age	Income <$50k	Income <$75k	Income <$150k
Loyalty to Car	5.1918		0.0154			1.356
Loyalty to Transit	5.5217		-0.0226			
Loyalty to Active Transportation	7.9432					
Transition from Car to Transit	5.1063		-0.0167		1.0374	
Transition from Car to Active Transportation	4.1731	-0.5508	0.0244			
Transition from Transit to Car	Not given	0.6674				
Transition from Transit to Active Transportation	2.0792			1.1607		
Transition from Active Transportation to Car	1.7652					
Transition from Active Transportation to Transit	2.8545	-1.2817		1.8354		

Variables	Children Present	No Children	Owned dwelling	Education up to College	Single-worker	Full-time dual-workers
Loyalty to Car	0.2923		0.5313	0.5326		0.7011
Loyalty to Transit				2.0185	0.7895	
Loyalty to Active Transportation		2.6984				
Transition from Car to Transit						
Transition from Car to Active Transportation						
Transition from Transit to Car	0.9332					1.1215
Transition from Transit to Active Transportation				1.2841		
Transition from Active Transportation to Car						
Transition from Active Transportation to Transit						

Variables	Increase in household income	Decrease in household income	Decrease in household car ownership	No car ownership	Increase in no. bedrooms	Decrease in no. bedrooms
Loyalty to Car						
Loyalty to Transit				0.8779		
Loyalty to Active Transportation				0.6479		
Transition from Car to Transit		1.195				
Transition from Car to Active Transportation		0.8724	0.7858			
Transition from Transit to Car						
Transition from Transit to Active Transportation		1.6794				2.6557
Transition from Active Transportation to Car	2.253					
Transition from Active Transportation to Transit					1.6597	

Variables	Moved from rented to owned	Moved from owned to rented	Birth of a child (1 yr lead)	New household formation	Addition of job (1 yr lead)	Addition of job (2 yr lead)
Loyalty to Car						
Loyalty to Transit					0.8519	
Loyalty to Active Transportation					-0.288	
Transition from Car to Transit		1.647				
Transition from Car to Active Transportation						
Transition from Transit to Car	1.416					
Transition from Transit to Active Transportation						
Transition from Active Transportation to Car	1.7979		1.427	2.6468		
Transition from Active Transportation to Transit						0.6536

Variables	Lost job (1 yr lead)	Lost job (2 yr lead)	Add. of car (same yr)	Traded car (same yr)	Distance to nearest transit station	Distance to nearest park
Loyalty to Car				0.782		
Loyalty to Transit					-0.3139	
Loyalty to Active Transportation						
Transition from Car to Transit	0.8313					
Transition from Car to Active Transportation						
Transition from Transit to Car			1.2939			
Transition from Transit to Active Transportation		2.5539				-4.9543
Transition from Active Transportation to Car						
Transition from Active Transportation to Transit						

Variables	Distance to CBD	Moved Closer to Work	Moved Closer to School	Moved Closer to Transit	Moved Farther from Transit	Moved Closer to Park Area
Loyalty to Car		0.2625				
Loyalty to Transit						
Loyalty to Active Transportation	-0.2859					
Transition from Car to Transit		0.5027				
Transition from Car to Active Transportation	-0.2566					1.9056
Transition from Transit to Car						
Transition from Transit to Active Transportation			2.3465		1.5473	
Transition from Active Transportation to Car						
Transition from Active Transportation to Transit				0.5071		

Variables	Moved Closer to CBD	Moved Farther from CBD	% Single-Family Detached	Land Use Mix Index	% Transit Trips	% Active Transport Trips
Loyalty to Car						
Loyalty to Transit						
Loyalty to Active Transportation						3.2395
Transition from Car to Transit						
Transition from Car to Active Transportation	1.2523					
Transition from Transit to Car	1.4586		0.0183	4.229		
Transition from Transit to Active Transportation						
Transition from Active Transportation to Car		1.246				
Transition from Active Transportation to Transit					7.8969	

Random Parameters Logit

Variables	Const.	Male	Age	Income <$50k	Income <$75k	Income <$150k
Loyalty to Car	9.824		0.0239			2.2741
Loyalty to Transit	10.9956		-0.0277			
Loyalty to Active Transportation	14.0003					
Transition from Car to Transit	10.1496		-0.0159		1.1875	
Transition from Car to Active Transportation	8.8482	-0.8945	0.0336			
Transition from Transit to Car	Not given	-4.326				
Transition from Transit to Active Transportation	6.4415			1.4632		
Transition from Active Transportation to Car	1.4161					
Transition from Active Transportation to Transit	7.2663	-4.1596		2.1196		

Variables	Children Present	No Children	Owned Dwelling	Education up to College	Single-worker	Full-time Dual-worker
Loyalty to Car	0.7325		0.8985	0.8449		0.339
Loyalty to Transit				2.5133	0.8512	
Loyalty to Active Transportation		3.5433				
Transition from Car to Transit						
Transition from Car to Active Transportation						
Transition from Transit to Car	3.3878					1.5023
Transition from Transit to Active Transportation				1.8856		
Transition from Active Transportation to Car						
Transition from Active Transportation to Transit						

Variables	Increase in household income	Decrease in household income	Decrease in household car ownership	No car ownership	Increase in no. bedrooms	Decrease in no. bedrooms
Loyalty to Car						
Loyalty to Transit				0.7883		
Loyalty to Active Transportation				0.6407		
Transition from Car to Transit		1.3222				
Transition from Car to Active Transportation		1.2154	1.2531			
Transition from Transit to Car						
Transition from Transit to Active Transportation		1.6389				3.0333
Transition from Active Transportation to Car	6.1449					
Transition from Active Transportation to Transit					2.0377	

Variables	Moved from rented to owned	Moved from owned to rented	Birth of a child (1 yr lead)	New household formation	Addition of job (1 yr lead)	Addition of job (2 yr lead)
Loyalty to Car						
Loyalty to Transit					0.7627	
Loyalty to Active Transportation					-0.626	
Transition from Car to Transit		1.9581				
Transition from Car to Active Transportation						
Transition from Transit to Car	4.6358					
Transition from Transit to Active Transportation						
Transition from Active Transportation to Car	2.0658		5.5368	4.7371		
Transition from Active Transportation to Transit						0.8414

Variables	Lost job (1 yr lead)	Lost job (2 yr lead)	Add. of car (same yr)	Traded car (same yr)	Distance to nearest transit station	Distance to nearest park
Loyalty to Car				0.999		
Loyalty to Transit					-0.3229	
Loyalty to Active Transportation						
Transition from Car to Transit	1.0167					
Transition from Car to Active Transportation						
Transition from Transit to Car			2.2094			
Transition from Transit to Active Transportation		2.9367				-6.0247
Transition from Active Transportation to Car						
Transition from Active Transportation to Transit						

Variables	Distance to CBD	Moved Closer to Work	Moved Closer to School	Moved Closer to Transit	Moved Farther from Transit	Moved Closer to Park Area
Loyalty to Car		0.2965				
Loyalty to Transit						
Loyalty to Active Transportation	-0.524					
Transition from Car to Transit		0.6934				
Transition from Car to Active Transportation	-0.3523					1.2207
Transition from Transit to Car						
Transition from Transit to Active Transportation			3.1335		1.4822	
Transition from Active Transportation to Car						
Transition from Active Transportation to Transit				0.8858		

Variables	Moved Closer to CBD	Moved Farther from CBD	% Single-Family Detached	Land Use Mix Index	% Transit Trips	% Active Transport Trips
Loyalty to Car						
Loyalty to Transit						
Loyalty to Active Transportation						3.875
Transition from Car to Transit						
Transition from Car to Active Transportation	2.105					
Transition from Transit to Car	2.5476		0.3543	1.3193		
Transition from Transit to Active Transportation						
Transition from Active Transportation to Car		3.2739				
Transition from Active Transportation to Transit					10.2416	