NCHRP 08-36, Task 141

Evaluation of Walk and Bicycle Demand Modeling Practice

Requested by:

American Association of State Highway and
Transportation Officials (AASHTO)
Standing Committee on Planning

Prepared by:

RSG
The RAND Corporation

May 2019

The information contained in this report was prepared as part of NCHRP Project 08-36, Task 141, National Cooperative Highway Research Program (NCHRP).
Special Note: This report **IS NOT** an official publication of the NCHRP, the Transportation Research Board or the National Academies.

AASHTO
THE VOICE OF TRANSPORTATION

Acknowledgements

This study was conducted for the American Association of State Highway Transportation Officials (AASHTO) Standing Committee on Planning, with funding provided through the National Cooperative Highway Research Program (NCHRP) Project 08-36, Research for the AASHTO Standing Committee on Planning. The NCHRP is supported by annual voluntary contributions from the state departments of transportation. Project 08-36 is intended to fund quick response studies on behalf of the Standing Committee on Planning. The report was prepared by RSG, with the RAND Corporation. The work was guided by a technical working group that included:

Dr. Xia Jin, Florida International University
Eunah Kang, The Port Authority of New York and New Jersey
Frank Law, California DOT
Dr. Jean Opsomer, Colorado State University
Michael Petesch, Minnesota DOT
Guy Rousseau, Atlanta Regional Commission
Lubna Shoaib, East West Gateway Council of Government
Dr. Marcelo Simas, Westat, Inc.

The project was managed by Lawrence D. Goldstein, NCHRP Senior Program Officer, with assistance from Dr. Anthony Avery, Senior Program Assistant.

Table of Contents

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

The Purpose of the Project

This project is an extension to previous NCHRP project 08-78 (NCHRP Report 770) "Estimating Bicycling and Walking for Planning and Project Development: A Guidebook." That study report, released in 2014, provides the following information:

- A general overview of walking and bicycling demand, in terms of the number of trips, trip characteristics, and traveler characteristics.
- A summary of what was known about factors affecting walking and biking, including the effects of land use, infrastructure, sociodemographic factors, and attitudes and perceptions.
- A description of best-practice methods (at that time) for estimating bicycle and pedestrian demand, introducing a range of tools from GIS-based methods to more complex discrete choice modeling approaches.
- A comparison of the properties of different approaches and guidelines for selecting and using an approach.

Since the release of NCHRP Report 770 in 2014, the number of agencies using advanced methods to predict bicycling and walking demand has continued to grow. The methods range from enhanced activity-based models to more traditional trip-based models.

The purpose of this project is to evaluate the current state of research and practice in regional pedestrian and bicycle demand modeling for both commute and noncommute trips by regional metropolitan planning organizations (MPOs) and state departments of transportation (DOTs) across the United States (US). The overall state-of-the-practice is surveyed and summarized, then compared to the state-of-the-art, as determined from recent academic literature and the most advanced recent or ongoing agency modeling projects. Gaps between common practice and the more advanced approaches are identified and communicated to practitioners, with an emphasis on what will be needed for agencies to address those gaps, in terms of data, expertise, and resources.

A Survey on the State-of-the-Practice

An on-line survey was carried out, inviting modelers from the roughly 400 regions MPOs and 50 state DOTs in the US. Responses were obtained from 72 MPOs and 24 DOTs. The responses to the on-line survey showed that just over half of the MPO respondents model both bicycling and walking trips, while only about 25% of DOT respondents model bicycling and walking trips. For both MPOs and DOTs who model bike and walk trips, about two-thirds of the agencies model them as separate modes, while the other third model them as a combined "non-motorized mode." It is important to keep in mind that the survey respondents are skewed toward the larger states and metropolitan regions that are more likely to have the interest and the resources to forecast walk and bike travel. All of the MPOs and DOTs with large modeling staffs model walk and bike trips, while the majority of agencies with fewer than three modelers do not. Thus, if we had obtained a 100% sample including all smaller regions and states, it would likely show that fewer than half of all MPOs and DOTs in the US model bicycle and pedestrian trip demand.

Both current practice and future interest in modeling nonmotorized travel are clearly more prevalent among MPO respondents than among DOT respondents. While most DOT respondents and interviewees indicated they are interested in bicycle and pedestrian travel issues and policies in their state, their statewide travel demand models often tend to be focused on longer trips—particularly auto trips on the state highways and other key roads. In cases where walk and bike trips are included in DOT statewide models, it is often so that they can be separated from auto trips, so as not to over-predict auto traffic. For MPO respondents, the strongest motivation for modeling nonmotorized trips is for regional program evaluation, although local program evaluation, evaluation of health benefits of active transportation, and social equity evaluation were also mentioned by almost half of the agencies that model bike and walk trips. MPOs who are not currently modeling walk or bike demand point to these same reasons as their motivation for wishing to model nonmotorized travel in the future.

Of the responding agencies that have models to predict nonmotorized trips, roughly half use a trip-based model, while most of the others use an activity-based (or tour-based) model. (Again we note that the survey sample is skewed toward larger regions and states who are more likely to use activity-based models.) The answers for modeling walk and bike trips are similar across the two modes, with two exceptions. First, most agencies who model nonmotorized trips model walk access to transit in some detail, while few currently model bicycle access to transit (although most agencies are interested in doing so in the future). Second, the percentage of agencies who assign bicycle trips to a network is twice as high as the percentage who assign walk trips to a network, although the interest in doing so in the future is fairly high for both modes.

The current use and future interest in adopting advanced methods like activity-based models (ABM) is strongly related to the size of the modeling staff. Of the responding MPOs with five or more modelers on staff, 90% have a current or planned ABM, and the other 10% are interested in developing one. Of the responding MPOs with only 1 or 2 modeling staff, the majority have no plan or interest to develop an ABM.

About 70% of responding MPOs collect bicycle count data, while just under 50% collect pedestrian count data. As was commented in some interviews and often found in practice, however, the amount of bicycle and pedestrian data collected is often meager in terms of the number of count locations and the length and frequency of count periods. This is particularly true when compared to the amount of count data available for cars and trucks. Several of the interviewees reported collecting additional bicycle and pedestrian counts as a necessary step toward modeling nonmotorized modes.

About 30% of the responding agencies currently use an all-streets network. About 20-25% currently use intercept/O-D survey data and GPS data for each mode. Most of those who do not currently use O-D or GPS data are interested in doing so in the future, although the interviews revealed that different modelers tend to have different concepts of what such data are exactly (or will be in the future), as well as different uses for the data.

About 25% of responding agencies said that they use microzone-level detail in their models. These tend to be the same agencies that use ABMs, which better accommodate using microzone-level detail.

For both MPOs and DOTs, the largest impediments to developing (improved) tools for modeling bicycle and pedestrian travel are the lack of availability of modeling staff time, as well as the lack of funding to hire more staff or consultants, and the lack of funding for more data collection and acquisition. Lack of clear guidance or training courses from the modeling/research community was mentioned as very important or somewhat important by about half of the respondents, but not as important as the lack of staff and funding (which would be needed to take advantage of such guidance or training). These sentiments were echoed in the interviews. Funding and staff time are limited resources and adding model capability competes against many other demands. Interviewees were looking for clear guidance on appropriate next steps to advance their models, and, while this information was not seen as large of a barrier as the resource constraints, the knowledge gap limits staff ability to articulate the value of advancing their models.

A Review of Literature on the State-of-the-Art

A methodical literature search was carried to review the most recent and relevant research on methods to model walking and cycling demand. The studies that were reviewed focused on a range of choice contexts, including route choice, mode choice, destination choice, and tour or trip generation. The studies have relied on a variety of different types of data, including stated preferences in hypothetical choice situations and revealed preference data from actual choices; the latter from household travel surveys, project-specific custom surveys, or smartphone apps or other devices that provide GPS data. Key behavioral factors have been identified consistently across those studies, falling into three main categories: (a) traveler characteristics. (b) infrastructure/network characteristics, and (c) surrounding land use characteristics.

One particular area of research focus has been on bicyclist route choice behavior. These studies and the resulting models tend to be technically complex, but they have produced useful results that have been implemented in a variety of ways in MPO models used in practice. Pedestrian route choice behavior has received less attention in both research and practice, but such research offers a similar potential for practical and useful results.

Another area of focus has been on attitudes and perceptions toward biking and walking—so-called “latent,” or “soft” variables. While such variables can be important, particularly in regard to perceptions of safety and stress, it is challenging to obtain data on such variables that can be applied in practical modeling contexts.

Key Gaps Between Modeling Research and Practice

While much of the published research uses advanced modeling techniques and innovative approaches, it is typically the case that the researchers do not have access to all of the data and experience that would be necessary to fully test their approaches in a practical modeling context such as an MPO regional travel forecasting study. Such practical studies typically require a good deal of auxiliary data such as zonal (and micro-zonal) land use data, network-based zone-to-zone matrices of travel times and costs, detailed data on the regional population, and count data to validate the model results. So, in general terms, the gap is one that exists in most areas of travel behavior modeling—the need to bring promising new ideas and methods “out of the laboratory”

and make them applicable within modeling tools that are accessible to MPO and DOT staff, their consultants, and, ideally, their constituent agencies such as county and city travel modelers. In the context of modeling walk and bike trip demand, there are particular gaps and challenges:

The need to accommodate greater spatial detail in practical models: Effective modeling of opportunities for walking and bicycling requires a greater level of spatial detail than the travel analysis zones (TAZs) used in most travel regional demand models. Compared to motorized travel, the trips tend to be shorter and more strongly influenced by the land use in the immediately surrounding area. Yet, the TAZ system is still required to allow modeling of motorized travel at the regional level, so the models must accommodate both levels of land use and zonal detail.

The need to use more network detail in practical models: Analogous to the point above, modeling walk and bike trips generally requires using an all-streets network containing details on all local streets, and also including details on bike lanes and bike paths of various types, pedestrian-only links (ideally including unpaved paths that are important shortcuts), and other key factors such steepness of grades and changes in elevation. It is rarely practical, to use such a detailed network for the entire region, however, so the model system must also accommodate multiple levels of network detail.

The need to have methods that are accessible for different types of users, in combination with different types of existing models: Most of the commonly used ABM frameworks are already capable of accommodating multiple levels of spatial detail and network detail, in ways are explained in the examples in Chapter 5. Trip-based models can also be adapted to use multiple levels of spatial and network detail through use of a two-stage approach. Examples are provided in the next chapter of both preprocessing and postprocessing approaches, where a module using more spatial and network detail to (better) predict walk or bike trips is run either before or after an aggregate trip-based model.

The need for methods to apply bicycle and pedestrian route choice models in practical ways: As mentioned above, route choice models can be quite complex to apply in their most rigorous form. Yet, the behavioral findings from these models can also be applied using simpler approaches, both to provide accessibility measures for mode choice models, and to assign bike or walk trips to networks.

The need to address perceptions regarding latent factors such as safety risk and health benefits: This is a challenge that has not been addressed to any great extent in practical forecasting models thus far. Although there are proxies for such factors, such as how separated Class 1 bike paths are preferred because they are safer and less stressful to use, there has not been a great deal of practical research to bring attitudinal variables into applied models. An example is the “safety in numbers” phenomenon. How might the perceived safety of bicycling improve as the number of bike trips on the streets and bike lanes increases?

The need for methods that are transferable from other regions: Some regions wish to model the availability of new types of bicycle or pedestrian infrastructure that currently do not exist within their region. As a result, there is no way to predict the behavioral outcome based on local

data. If models of bicycle and pedestrian travel demand can be shown to be transferable across regions, then such regions can use models developed in other regions.

The need for accessible and transferable software tools: This is a general need within the travel demand modeling profession which amplifies the needs listed above. It is much easier to transfer methods and/or models developed elsewhere if there are software tools or modules designed with ease of use in mind.

Several practical models and tools addressing the gaps listed above do exist. However, they are often not well-documented in the literature, given that the agency modelers and contractors who carry out the modeling projects do not have a great incentive to publish in journals. As a result, much of the documentation is in model documentation reports and memos that are often not accessible in literature reviews. Much more work is presented at conferences, such as the various TRB conferences, and are available in the form of full papers or slide presentations. Chapter 5 of this report is more technical than the other chapters, providing several examples of how the gaps identified above have been addressed to advance the current state-of-the-practice in modeling bicycle and pedestrian travel demand. In our in-depth interviews, several of the respondents indicated that they would find a focused technical discussion of such examples to be a useful product of this study.

Recommendations for Trip-based Model Contexts

Although most of the examples provided in Chapter 5 are for ABMs, it is possible to achieve many of the same types of improvements in more traditional aggregate trip-based models. Key areas for potential improvement are:

- Including walk and bike as separate nonmotorized modes in mode choice. The impedance measures for these modes can be based on simple network shortest path distance measures, although we suggest enhanced measures below.
- Including car ownership variables in the utility for walk and bike (and transit), preferably using a car ownership model that is integrated into the model system. Segmenting households into three segments is recommended: (a) no cars in the household, (b) 1+ cars in the household, but fewer cars than adults, and (c) 1+ car per adult in the household. (Note: Cars per worker can also be used instead of cars per adult.)
- Adding geographical detail to the zone system by using smaller TAZs, particularly in denser areas with the highest potential for walk and bike trips.
- Adding detail to the network, moving in the direction of using an all-streets network. (This is most feasible for regional models that use finer spatial detail on the zone system, and the least feasible for statewide DOT models or MPO models for large urban regions.)
- Using smaller TAZs and/or more network detail to also model walk access to transit more accurately.
- Adding walk- and bike-specific attributes to the networks to the extent possible, such as existence of various classes of bicycle lanes and paths, measures of gradient or changes in elevation, and identification of barriers to walking and cycling, such as freeways and rivers.

- Using more land use variables in the models, such as mixed-use measures, street connectivity measures such as intersection density, and presence of public parks. Using consistent buffering methods to measure these variables is also recommended.
- Using generalized distance or time measures from route choice models instead of shortest distance alone to select the best walk and bike paths and set their utility in mode choice models. The enhancements to the Phoenix (MAG) trip-based model (RSG, 2018) are an example of how this was done for the bike mode, as well as for bike access to transit.

Preprocessing tools

Preprocessing approaches exist, such as that described by Clifton, et al. (2016). Such an approach is most suited for using fine-grained microzones to model walk trips before processing the nonwalk trips using the existing trip-based model. It is suited for walk trips more than for bike trips because it focuses on short trips in small areas, without explicitly modeling the attractiveness of competing modes on the street network.

Postprocessing tools

The tool created for the Monterey Bay MPO (Hood et al, 2014) is a good example of a transferable approach, providing a user-friendly interface to specify future bicycle network scenarios, and then using a bicycle route choice model to evaluate the resulting change in the attractiveness of the bike mode for each TAZ-pair, and applying elasticities to the trip tables output from the regional trip-based model to attract trips from (or lose trips to) the competing modes of auto, walk, and transit. The software tool also evaluates changes in emissions resulting from the mode shifts across all zone pairs.

Other postprocessing methods, such as that used by the Capitol District MPO in Albany, NY, analyze the trip tables resulting from a trip-based model by distance and purpose to gauge the potential for walking or cycling in specific corridors or subareas, or to identify which corridors or subareas have the most potential. The GIS-based accessibility tools discussed in NCHRP Report 770 could also be used for this purpose, in combination with trip tables predicted from an existing travel model. As passive origin-destination data improves in quality and becomes more affordable, such methods could also be applied to origin-destination matrices from passively collected data instead of trip tables produced by models. Such approaches are useful as quick-response methods to assess market potential, in contexts where more elaborate forecasts are not required.

Recommendations for Activity-Based Model Contexts

In many ways, the list of recommended improvements for ABMs is similar to the list provided for trip-based models above. However, the household-based microsimulation structure of ABMs provides more flexibility in how the improvements can be implemented. Key recommended enhancements are:

- ABMs have the flexibility to add geographical detail to the model system by using a second layer of geography, typically called microzones (MAZs). A convenient way to create microzones is to use the intersection of Census blocks and TAZs, although using

parcels or some aggregation of parcels is also possible. As with trip-based models, using more and smaller TAZs can also be useful.

- Adding network detail to a regional model system by using an all-streets network, which can be processed at the MAZ level to provide accessibility measures for short-distance trips, which include most walk and bike trips. As with trip-based models, adding more local streets to the TAZ-based planning network is useful as well, particularly for modeling bicycle trips.
- Adding walk- and bike-specific attributes to the networks (both the all-streets and planning networks) to the extent possible. This includes existence of various classes of bicycle lanes and paths, measures of gradient or changes in elevation, and identification of barriers to walking and cycling, such as freeways and rivers.
- Using land use variables such as mixed-use measures, street connectivity measures such as intersection density, presence of public parks, and residential and employment density, particularly in the mode choice utility equations for walk and bike. Using distance-decay buffering methods based on on-street distances to measure these variables is also recommended. Use of composite functions of these variables is recommended in model estimation to address the issue of high correlation between the variables.
- Using generalized distance or time measures from route choice models instead of shortest distance alone to select the best walk and bike paths and set their utility in mode choice models. Using logsum measures from a fully-applied multipath bicycle route choice model is another option, although this involves greater complexity in programming and longer computation time.
- The structural flexibility of ABMs makes it feasible to use separate zone systems for the auto and transit modes, using a separate zone system of transit access points (TAPs) located at transit stations and stops (areas) to improve the modeling of walk (and bike) access to transit. TAP-to-TAP transit time and cost matrices only include the transit path itself, but not the access and egress portions of transit trips. MAZ-to-TAP walk distances are combined with the TAP-to-TAP skims to find the best walk-transit-walk path between any MAZ origin-destination pair. This method can be extended to various options for bike access to transit as well. This is a more major change to the model system than the others listed above, and is mainly recommended for regions with extensive, multimodal transit systems. In addition to improving the modeling of walk and bike access to transit, it has the benefit of more accurately modeling the transit network and transit use.

The model enhancements in the above list are already implemented in some transferable ABM software platforms. If these options do not already exist in the ABM software platform being used, it may require considerable work to add them. If they do already exist in the platform being used, the extra work for the agency is primarily in specifying, building, and maintaining the additional input data that is required for these enhancements, both for the base year and for forecast year scenarios. For forecast years, it can be appropriate to leave the all-streets network used for short-distance calculations as-is, since these calculations do not use freeway links and are not sensitive to the capacities on other arterials. The exception to this is a recommendation to

add MAZs and network detail in greenfield areas that are sites for extensive development in future scenarios. (This can also apply to adding TAZs and planning network detail in such areas.)

Software advances

Clearly, the recommendations given above are more likely to be adopted if they can be implemented relatively easily within preexisting, well-documented, user-oriented software packages. The subject is discussed in detail in Chapter 6 to indicate that several software platforms are moving toward greater ease of use, but there is still room for great improvement.

Recommendations for Future Research

Chapter 6 concludes with recommendations of promising areas for future research:

- Research into data standards and transferable data and data tools
- Cross-regional studies: transferability of walk and bike behavior and models
- Use of passive "big data": how to better impute and expand walk and bike trips
- Further research into the separate effects of aging and generational change (age cohorts) on the propensity of walking and biking
- Methods to better incorporate latent attitudinal variables
- A new competing mode: transferability of the methods to shared electric scooters
- The role of state DOTs in advancing the state-of-the-practice

CHAPTER 1. BACKGROUND AND OBJECTIVES

1(A) THE PURPOSE OF THE PROJECT

This project is an extension to previous NCHRP project 08-78 (NCHRP Report 770) "Estimating Bicycling and Walking for Planning and Project Development: A Guidebook." That study report, released in 2014, provides the following information:

- A general overview of walking and bicycling demand, in terms of the number of trips, trip characteristics, and traveler characteristics.
- A summary of what was known about factors affecting walking and biking, including the effects of land use, infrastructure, sociodemographic factors, and attitudes and perceptions.
- A description of best-practice methods (at that time) for estimating bicycle and pedestrian demand, introducing a range of tools from GIS-based methods to more complex discrete choice modeling approaches.
- A comparison of the properties of different approaches and guidelines for selecting and using an approach.

Since the release of NCHRP Report 770 in 2014, the number of agencies using advanced methods to predict bicycling and walking demand has continued to grow. The methods range from enhanced activity-based models to more traditional trip-based models. Most are for regional metropolitan planning organizations (MPOs), while a few are for state departments of transportation (DOTs) or for local city or county agencies.

A reason for the growing interest in predicting walking and bicycling trips is that these modes are often becoming higher profile in local and regional transportation planning, for several reasons:

- **Public health benefits:** The physical activity involved in walking and bicycling can reduce the incidence of obesity and chronic disease in the population. (Note: The scope for this project does not include a detailed treatment of the evaluation of health benefits.)
- **Equity and accessibility**: Walking and bicycling are generally more affordable and more widely available across the population compared to driving or using transit.
- **Reducing traffic congestion**: Bicycle and pedestrian trips can substitute for auto trips in some circumstances, reducing traffic flow, and perhaps reducing the need for new road capacity or parking.
- **Environmental benefits**: Walking and bicycling produce little or no pollutants or greenhouse gas emissions and require less paved land for roads and parking.
- **Strong public advocacy groups**: In many regions, groups are committed to improving bicycle and pedestrian infrastructure and safety. Advocacy is often focused on the health and safety of the younger population, including Safe Routes to School programs.

The purpose of this project is to evaluate the current state of research and practice in regional pedestrian and bicycle demand modeling for both commute and non-commute trips by regional MPOs and DOTs across the United States (US). The overall state-of-the-practice is surveyed and

summarized, then compared to the state-of-the-art, as determined from recent academic literature and the most advanced recent or ongoing agency modeling projects. Gaps between common practice and the more advanced approaches are identified and communicated to practitioners, with an emphasis on what will be needed for agencies to address those gaps, in terms of data, expertise, and resources.

1(B) THE STRUCTURE OF THE PROJECT AND THE REPORT

The first project task was to carry out a literature review of recent advances in the state-of-the art in predicting the travel choices of cyclists and pedestrians, including mode choice, route choice, and other aspects of choice behavior. Chapter 2 provides an overview of the findings of the literature review, while the literature review process is described in Technical Appendix A.

The second task involved carrying out an internet-based survey of MPO and DOT modeling staff across the US. The questions ask about the agencies' motivation for modeling walk and bike trips, the methods and data used to model demand for each, and any key impediments to modeling walk and bike demand. The final sample obtained includes responses from 72 MPO modelers and 24 DOT modelers. Chapter 3 provides an overview of the survey results. In-depth follow-up interviews were carried out with 12 of the survey respondents, selected to provide a mix of MPO and DOT modelers, who use a range of approaches to modeling walk and bike demand—ranging from using advanced activity-based models to not modeling walk or bike trips at all. The interviews were done to understand better the background and reasons behind the answers the respondents reported in the on-line survey. Chapter 3 provides summary information from the interviews. Information from the interviews is also used to provide and highlight examples in the remaining chapters.

In Chapter 4, we synthesize the findings of the literature review, the on-line survey, and the in-depth interviews, with project team's recent experience in predicting walk and bike trip demand for several MPOs, counties, and cities in practice. Based on the literature on the state-of-the art research, as well as recent developments in travel demand modeling and network modeling, we contrast the latest research methods and findings with the current state-of-the-practice to identify the most important gaps.

In Chapter 5, we provide several examples of methods used to predict pedestrian and bicycle demand by various government agencies in the US and elsewhere. Although a range of approaches is covered, the most emphasis is given to examples that illustrate specific advances in the state-of-the-practice for MPO regional models. Note that several of these examples are not found in published literature, as some are based on modeling projects that have recently been completed or are nearing completion. For such applied projects, the documentation often consists only of technical memos or model user guides, with little context provided about what is new or different about the approach used. Thus, Chapter 5, the longest chapter of the report, provides a unique and up-to-date overview of recent advances in modeling the demand for non-motorized trips.

Finally, Chapter 6 summarizes the range of modeling approaches and recent advances discussed in the previous chapters. It provides separate recommendations for trip-based model users and

activity-based model users and includes some recommendations for which approaches may be best suited for specific agency modeling needs and capabilities. As software tools are critical, the chapter provides a discussion and recommendations specific to software. Ideas for disseminating the information and recommendations in the report are also provided. The chapter ends with some suggested topics for further research. One topic is the use of passively collected data sources to support modeling of walk and bike travel patterns. Another topic is the emerging use of shared electric scooters, which could be substitutes or complements to walking and biking and will require some of the same modeling approaches to predict future demand.

1(C) AN OVERVIEW OF IMPORTANT MODELING TERMINOLOGY

This report assumes that the reader has a basic knowledge of travel demand modeling and forecasting. For readers not so familiar with the subject, this section provides a brief overview of important concepts and terms.

Networks: Most travel demand models used for regional and state planning use road networks (and some use transit networks as well). Road networks are made up of nodes (intersections) and links (road/street segments). Each direction of travel on a two-way street is usually treated as a separate link. In most models, the "planning network" is not an "all-streets network." The planning network represents a subset of all roads and streets, including highways and arterials, but omitting many local streets. The network needs to be detailed enough to represent travel routes between all travel analysis zones (TAZs), with connector links from each TAZ to the network typically used to approximate local streets.

Each trip is modeled to begin in an origin TAZ and end in a destination TAZ. A network software package such as TransCAD, Cube, EMME or Visum is typically used to determine the best path(s) through the network for each origin-destination (O-D) zone pair. The speed and travel time on each link are a function of the modeled vehicle flow on the link within a specific time period compared to the capacity of the link—the number of vehicles that can traverse that link within the specified time period. The network software is used to perform two main functions for travel demand models: (a) <u>assignment,</u> in which all trips are assigned to use specific routes through the network, and (b) <u>skimming</u>, in which travel impedance measures such as travel time, distance and tolls are summed across all links and intersections in the route for each O-D TAZ pair, and written out in the form of TAZ-to-TAZ skim matrices.

As discussed in later chapters, road networks used to model walk and bike trips can be the same as the networks used to model auto trips, although walk and bike trips are usually excluded from using freeway links, but they may use bike-only links (bike paths and lanes) and pedestrian-only links that are not available to other travel modes. In the large majority of models, assignment of walk and bike trips to the network is not capacity-constrained, so the number of walk or bike trips using the network does not affect the travel impedance for those modes.

Trip-based models: The majority of travel demand models used in practice are trip-based models. They are often called "four-step models," as most such models include the steps of trip generation, trip distribution, mode choice, and network assignment. They may include other "steps" as well, such as auto ownership models or time of day choice/peak spreading models.

Trip-best models are often referred to as "aggregate" models because they treat all households within a given population segments living in a particular TAZ as one aggregate group. The household segmentation variables, such as household size, income group, or number of workers, are the only socio-demographic variables available to the model. In the distribution (destination choice) models, the key variables are land-use attraction variables, such as TAZ employment in various categories, and travel impedance variables from the TAZ-to-TAZ network skims. In the mode choice models, the key variables are the TAZ-to-TAZ network skims of the travel times, distances or costs for each mode. The modes typically include auto and transit. If walk and bike are included, they can be included as separate modes or as a single composite "non-motorized" mode.

Trip-based models are usually scripted within the same network package that is used for traffic assignment, providing the convenience of using a single software platform. The model structure within most network packages is designed to loop across the TAZs and predict the travel for each household segment in a given TAZ to each other TAZ by each mode. The output of the model is in the form of TAZ-to-TAZ trip matrices (often called "trip tables") with separate matrices for each mode and time of day period. (Trip matrices can also be produced for different trip purposes or limited socio-demographic segments.)

Tour-based models: Tour-based models differ from trip-based models by considering sequential trips in a trip-chain as a basic unit of travel. For example, a home-based work tour can be a trip chain that includes a trip from home to work, a trip from work to the supermarket on the way home, and then a third trip from the supermarket back home. Every tour has at least two trips, but some also include intermediate stops which generate additional trips. Some tour-based models are similar to the aggregate structure of trip-based models, but modified to predict tour generation instead of trip generation. In that case, additional model steps are used to predict the generation and the location of any intermediate stops on the tours, also using the aggregate TAZ-based model structure. This model form is often referred to as a "hybrid tour-based" model (Bernardin and Conger, 2010).

Tour-based models can also be simplified implementations of the disaggregate activity-based model framework described below—simplified by not including models to schedule different tours within a travel day.

Activity-based models: In addition to modeling tours and trips, activity-based models (ABM) extend the framework to model an entire travel day, with models to schedule tours and trips consistently across an entire day (so that a person is not predicted to be in two places at the same time). While all ABMs enforce this consistency at the person-day level, some also model explicit interactions between different household members, including joint tours and parents chauffeuring children.

ABMs use a disaggregate microsimulation approach, simulating a travel day for each individual household and person in a synthetic population, which is created to be representative of the actual population along important geographic and socio-demographic dimensions. The output of the ABM is a list of individual predicted trips, including all key attributes such as origin, destination, time of day, mode and purpose. The trip list is then aggregated into trip matrices

which are input to a network software package for assignment to the network, and for producing skim matrices of travel times and costs that are fed back to the ABM.

Because this disaggregate simulation approach does not follow the aggregate zone-based structure of the network software packages, ABMs require using a separate software platform rather than scripting the model code within the network software. The need to use a new software platform adds to the amount of effort and learning needed to use an activity-based model, as compared to a trip-based model. As described in later chapters, however, the flexibility of the ABM microsimulation structure makes it possible to implement several enhancements for modeling walking and cycling trips that are not feasible within a trip-based model.

CHAPTER 2. STATE-OF-THE-ART MODELING OF PEDESTRIAN AND BICYCLE DEMAND—A LITERATURE REVIEW

2(A) INTRODUCTION

The first research task for this project was to carry out a targeted literature review to identify the 'state-of-the-art' in terms of modeling walking and bicycling demand, particularly for regional forecasting models. Technical Appendix A provides a description of how the literature review was carried out.

Note that although we discuss modeling walk and bicycle trip demand generally together, we emphasize that the characteristics of these trips and modeling needs for both may be quite different, and we highlight specific differences where relevant.

Below we discuss findings across three key areas:

- Data.
- Geographical specificity.
- Model responses, including trip generation, mode and destination choice, route choice.

The most attention is given to the latter topic, for which the most literature is available.

2(B) DATA

Availability of data on travelers' behavior is critical for modeling bicycling and walking trips. The literature review focused on modeling and not on data per-se, although the modeling studies that were considered relied on various types of data, including household travel surveys, intercept surveys, Global Positioning System (GPS) surveys, network data, land-use data, and socio-economic data. All of those types of data are discussed in later chapters of this report. In this section, we provide some discussion of GPS data as a particular type of data that was used for several of the behavioral studies reviewed.

GPS Data

In the last decade, GPS data collection methods have allowed for more accurate reporting of non-motorized trips, particularly short trips that may be forgotten in more traditional travel surveys (Clifton et al, 2016; Clifton and Muhs, 2012). A key benefit of GPS methods is that they can record information on non-motorized trips that are made by individuals as well as the routes used for the journey. Li (2017) notes that this saves both time and money, and the route data collected are more accurate than those from traditional surveys. A potential shortcoming for GPS data that are collected completely passively, i.e. without any input requirement from the traveler, is that assumptions are required to indicate what mode has been used for the journey as well as the purpose for that journey. The quality of such assumptions will affect the quality of the resulting models. Also, models that rely on passive data collection only may not collect important data on variables describing the context of the journey, for example whether the traveler is traveling in a group, their socio-economic characteristics, etc. Alternatively, GPS data may be collected as part of a wider travel survey, allowing travelers to check journey characteristics to confirm the mode

of travel and journey purpose and to report explicitly other relevant journey characteristics as well as their socio-economic and household characteristics.

As with all data collection exercises, it is important that GPS data collection methodologies sample travelers who are representative of the population of interest. Our literature review has found that—depending on the sampling methodology—GPS survey samples (in this case of cyclists) can be skewed towards more experienced cyclists, who may have different preferences to the general population of cyclists, for example they may be less interested in bicycling facilities, which would result in a lower valuation of such facilities relative to bicycling on roads.

The combination of GPS data collection methods in conjunction with increasing availability of detailed open-source data on walk/cycle networks, routes and land uses has spurned a proliferation of models that are able to quantify the importance of infrastructure, land-use, topography, socio-demographic variables and attitudes on route, mode and destination choices. Although mapping methodologies for linking GPS data to cycle network links remains ad hoc across studies.

Stated Preference Data

A few of the papers included in the literature search used stated preference methods to quantify the value of cycle infrastructure (Maldonado-Hinarejos et al. 2014; Mohanty and Blanchard 2016; Sener et al. 2014); Wardman et al. used both revealed preference and stated preference data jointly to exploit the benefits of each data collection method. The benefit of stated preference approaches is that they can be used to quantify the value of attributes that are not available in the existing network. The Maldonado-Hinarejos et al. (2014) and Wardman et al. (2007) studies also incorporate attitudinal variables (discussed later), although attitudinal data is not explicitly aligned with SP studies only (Broach, 2016; Montini et al., 2016; Shen et al. 2014; and Subhani et al. 2013 all provide examples of using attitudinal variables with revealed preference data).

2(C) GEOGRAPHIC SPECIFICITY

A key issue for modeling demand for non-motorized trips is representation of the quality of the environment for walking and bicycling at a fine level of detail; for example, to reflect whether a route or mode choice alternative incorporates sidewalks or cycle lanes, is on a busy street, in an area with high density of work places and homes, etc. And one of the key limitations of adequately representing walking and bicycling in regional travel demand models has been the spatial scale of analysis. Transportation analysis zones (TAZs)—the unit of geographical analysis in traditional travel demand models—have tended to be defined to fit well with census geographies and to minimize the computational modeling burden through smaller trip matrices (Clifton et al., 2016). Often, the level of geographical specificity is not detailed enough to quantify the drivers and characteristics of non-motorized travel – indeed a substantial proportion of walking trips may occur as intra-zonal trips (Clifton et al. 2016). As a result, TAZ-based models can yield poor estimates of pedestrian travel demand and walking distances traveled (Clifton et al., 2016). Furthermore, the spatial granularity used for the zonal system must be

consistent with the specificity of the transport network. Larger zones reduce the ability to consider lower functional-class streets that may have sidewalks or be striped with bike lanes.

Increasing computational processing power means that smaller TAZs with more detailed representation of walking and bicycling are more able to be accommodated in large-scale models (Clifton et al. 2016). Rather than generalizing land use and travel at the level of TAZs it is possible to discern activities at parcel-level of detail—allowing for much more detailed characterization of the travel environment and factors that affect non-motorized travel—which is particularly important when trying to understand and predict demand for these journeys (Kuzmyak et al., 2014). However, trade-offs between increasing numbers of smaller zones and detail in other aspects of the travel demand model, in terms of number of behavioral responses, linkages between model components, etc. are still important and our review has uncovered several proposed approaches to simplify regional model structures to account for increased detail in the geographical specificity. Several different approaches are discussed in the following section describing typical responses and structures in regional travel demand models.

2(D) MODEL STRUCTURE AND RESPONSES

Below we discuss treatment of walk and bicycling across key components of regional models, i.e. trip (and tour) generation, mode choices, destination choices and route choices.

In general, NCHRP Report 770 (Kuzmyak et al., 2014) recommends using a 'choice-based' modeling framework where traveler behavior is assumed to be the result of rational decision-making in which the traveler chooses from a set of alternative modes (or routes or destinations), where factors like the built environment, the infrastructure network and facilities as well as other natural environmental factors (discussed further below), as well as characteristics of the traveler, influence decisions of whether to walk or cycle. Ideally, such models would be developed from (disaggregate) data of individual travelers' decisions, which provides the best opportunity to quantify the relative importance of different factors on travelers' decisions.

Our review has identified several studies that use a discrete choice framework to quantify influences on travelers' decisions to walk or to cycle, taking account of infrastructure, land-use, topography, socio-demographic variables and attitudes.

In most cases, the studies focus on particular choice decisions that affect walking and bicycling such as generation, mode, or route choice. However, some studies have considered the interactions between different choice decisions. For example, Pinjari et al. (2011) developed a model system that represented cycle ownership together with decisions on residential location, car ownership and mode choices for commuting as a function of network, socio-economic, land use and other variables. Singleton et al (2012) considered how best to introduce walk as a travel mode to regional travel demand forecasting models, considering different placements in the overall model structure taking account of availability of cycle choice and network data.

Units of Analysis

The advanced modeling approach recommended in NCHRP Report 770 involves using "tours" (home-based trip chains) rather than individual trips, on the basis that tours take into account

decisions both about the outward and return journeys and explicitly represent trip chaining, which has an important bearing on mode use. They note that multistop tours are generally made by auto, while simple tours are more likely to be made by walking, biking or transit, and that such differences should be taken into account in travel demand models.

Modeling Trip and Tour Generation

Generally, regional models contain a component to predict the total number of trips (or tours) that individuals within a specific zone will make, given their socio-economic characteristics. It is often important that such models incorporate non-motorized trips, for the various reasons listed earlier

NCHRP Report 770 recommends that tour and trip generation models take account both of the traveler's socio-economic characteristics, as is usually done, as well as land-use variables, including parking availability and cost, intersection density, residential density, measures of land-use mix, and both automobile and non-motorized mode accessibility measures. Table 2.2 (below) contains land-use variables that have been used across the studies, both for route choice, mode choice and trip generation. It is interesting that none of the tour or trip generation models that we reviewed incorporate accessibility as measured directly in the mode and destination model components.[1]. Instead we have observed trip generation models which explicitly take account of the network conditions, including some sort of accessibility measures (NCHRP Report 770). In contrast, Khan et al. (2014) do include accessibility terms measured by model logsums in their model of non-motorized trip making (trip generation) and find that the number of non-motorized trips made is positively related to accessibility for non-motorized trips and negatively related to accessibility for single-occupancy vehicle accessibility. However, it is not clear how this model is then used; given subsequent models of mode choice include all modes, not just non-motorized ones.

In terms of geographical specificity, Clifton et al. (2016) recommend that trip generation models be developed at a much more detailed level of geographic specificity ("pedestrian analysis zones," or PAZs, rather than TAZs). This is consistent with the land-use parcels approach of NCHRP Report 770 and Khan et al. (2014).

A further innovation described in NCHRP Report 770 is the prediction of simple and complex tours in the trip generation phase, the latter which are less attractive for walking or bicycling.

[1] In a hierarchical logit model, the number of trips (or tours) can be linked to overall accessibility across all modes (the logsum over modes and destinations), which incorporates both the quality of the network conditions and destination opportunities therefore reflecting that more trips will be made to and from more accessible zone pairs and fewer trips will be made to and from less accessible zones and that accessibility will influence the number of trips or tours made in future. Note that the most commonly used activity-based model frameworks in the US (DaySim, CT-RAMP and TourCast) do use logsums over modes and destinations to model tour generation and daily activity patterns.

Mode Choice and Destination Choice

NCHRP Report 770 elucidates two specific challenges of developing mode and destination choice models incorporating walking and bicycling:

- Using disaggregate models that represent mode and destination choices from the perspective of the individual traveler, rather than as spatial aggregations of households in TAZs.
- Accounting for destination and mode choices as simultaneous choices.

We have not observed any papers reporting estimation of mode choice models incorporating walking and bicycling modes (at a detailed level of spatial specificity) and destination choice models simultaneously, although we are aware of such models being applied in Europe and Asia.

A key challenge of mode and destination choice models is how best to structure a model with increased detail in terms of the level of geographic detail in the zone system and networks, while keeping the complexity and computational burden of the model at a practical level. We saw several different approaches in the literature, briefly described below.

The approach proposed by Clifton et al. (2016) first predicts the traveler decision to walk or not to walk at a high level of geographical specificity and then develops separate models of destination choice for walk trips (at a more detailed level of geographical specificity) and mode and destination choices for non-walk trips. The benefit of such an approach is the ability to represent detailed information in the choice to walk or not. The disbenefit is that walk or not choice does not take account of the characteristics of competing modes, for example the likelihood of choosing to walk is not impacted by increasing congestion levels for car or transit journeys or increased transit fares. Further, the structure of the model—first predicting the mode choice to walk or not (walk mode choices), then predicting destination choices and then predicting mode choices for non-walk trips—seems a bit at odds with traditional model structures. Moreover, the models of mode and destination choice are estimated sequentially.

NCHRP Report 770 proposes an ‘enhanced’ approach for trip-based models with larger zones (this is also the approach reported in Khan et al. (2014)) whereby trips are split between intrazonal and internal trips (after trip generation) taking account of car and non-motorized vehicle accessibility, complexity of routes, and socio-economic characteristics, including license holding. Separate mode choice models are then developed for intrazonal and interzonal trips. This may be a useful distinction, although its usefulness will depend on the size of the zones in the model, where the value of such a distinction will decrease as the size of the zones decreases.

A second approach is described in NCHRP Report 770 which involves the development of detailed mode choice only models to predict choice of mode (walking, bicycle, transit or auto) for different trip purposes at a detailed geographical level of specificity (“microzones,” which may be individual land parcels or other units that are smaller than typical TAZs, such as census blocks). They describe two model approaches:

- Origin-Destination – incorporating information on land-use, network and accessibility at both the trip origin and destination (if the location of the trip destination is ‘known,’ i.e. if

destination choice is above mode choice in the model structure, e.g. for a work or school trip), as well as the origin-destination travel time or cost.

- Origin only – includes information on land-use, network and accessibility at the origin end only; using this version is appropriate when the location of the destination is 'unknown,' i.e. if destination choice is below mode choice in the model structure, e.g. for shopping or a personal business trip.

In all cases, there is little discussion of how the quality of the proposed structures compares to others and no formal comparison of different model structures or approaches.

Little evidence exists on what nesting structures have been used or tested. An exception is Mahmoud et al. (2015) who find with higher cross-elasticities between non-motorized modes.

Travel Mode Availability

In models of mode choice, Broach (2016) discusses the importance of specifying the 'availability' of travel modes, to ensure that the resulting model coefficients are not biased. He notes:

- Universal choice set (all modes always available), are often used, an assumptions that can bias parameter estimates significantly.
- Rule of thumb distance thresholds, may be ok, but often these are quite long.
- Sample-based time/distance thresholds, which may be more behaviorally defensible.

He notes that bike availability is not often used in specifying availability for bicycle trips or tours. Such an availability condition may become less relevant with bike sharing schemes and otherwise would require inclusion of a bike ownership model. Also, the cost of buying and operating a bicycle is not likely to be an impediment to bicycle use, while many people own bicycles but rarely, if ever, use them. Thus, the strength and direction of causality between bicycle availability and bicycle use is open to question.

Intrazonal and Interzonal Trips

As noted earlier, using TAZs means that a substantial proportion of walk / cycle trips are intrazonal trips, which are not represented well in large-scale travel demand models. The approach by Khan et al. (2014) explicitly incorporates a step dividing trips into intrazonal and interzonal trips based on traveler socio-economic and land-use and network characteristics and then performs mode split for each group (Khan et al. 2014; Kuzmyak et al. 2014). However, if the geographical specificity of the model is detailed enough, this should not be required.

Walk and Bike Trips Made to Access Transit

Incorporating specific walk and bike access alternatives to transit options will add to the complexity of mode choice models, but may allow for much better representation of walking and bicycling demand.

Mohanty and Blanchard (2016) explicitly incorporated walk and cycle trips to transit alternatives, using mixed-logit choice models. They found that the likelihood of walking and bicycling to access transit alternatives was influenced by:

- Socioeconomic variables, e.g. age, gender.
- Network factors, e.g. sidewalk width, suitability of crossings, average trip slope.
- Environmental and facility factors, e.g. access to trains and space in transit vehicles for bikes and the presence of covered bike parking.

Halldórsdóttir (2015) modeled choice of access and egress transport mode in the Copenhagen Region for rail journeys at both the home end and the activity end. He found that the home end of trips had a much larger bicycle, car driver and car passenger mode share while the activity-end had much larger walk mode shares, highlighting the importance of this distinction. Bicycle parking and the ability to bring your bicycle on the train were found to be significant factors in cycle mode choice.

Route Choice

Developing route choice models for walking and bicycling can help quantify demand for walking and bicycling facilities. Moreover, they can inform policymakers about the relative importance of network and land-use characteristics for route choice.

Our literature review contained several studies developing route choice models for walking and bicycling (Montini et al, 2017; Subhani et al, 2013; Zimmermann et al, 2017; Broach et al. 2012; Hood et al. 2011; Li 2017; Sener et al. 2010; Shen et al. 2014; Yeboah & Alvanides 2015; Halldórsdóttir 2015). The papers identified several challenges in developing route choice models for these modes.

First, there is an issue of how to treat recreational and exercise trips, where longer routes may be intentionally chosen by travelers, which could result in biased relative valuations of route characteristics, and where travelers may make trips starting and finishing at the home where they do not visit any non-home destination which makes them difficult to represent in conventional demand models. It would seem that it was important to include such trips in the model if the aim of the modeling study is to quantify demand for walking and bicycling infrastructure or if walking and bicycling congestion is an important component of the study. However, in such cases it is important to identify those traveling for recreational and exercise trips from those traveling for other purposes, particularly for commute purposes, where travelers may be much more sensitive to time or distance.

Second is the challenge of generating appropriate routes for the choice set, which is a common challenge for route choice modeling, but that may be much more important when generating bike or walking routes, which may depend much more heavily on the quality of the network than for car where the shortest distance or time may be more important.

There does not appear to be a ‘best’ in route choice set generation as the pros and cons of different methods need be weighed on a case by case basis. Li (2017) summarizes existing methods for route choice with their relative benefits and limitations, shown in Table 2.1. Trade-offs to consider include the ease of implementation, computational efficiency, omission of plausible alternatives, ability to define penalty factors, level of overlap, reasonableness and meaningfulness of the route choice set.

Third, there may be substantial heterogeneity between travelers' route preferences for those who choose to walk or cycle. For example, Subhani et al (2013) found substantial differences between confident and less confident cyclists in terms of route choice. Interestingly, while we note that there could be substantial heterogeneity in route choices for walkers and cyclists, the studies that we reviewed did not find much evidence on route choice differences due to socio-economic characteristics. For example, only one study (Sener et al. 2010) found gender to be significant out of four studies that tested a gender term (Hood et al. 2011; Li 2017; Halldórsdóttir 2015; Sener et al. 2010). Only Li (2017) was able to estimate a significant age parameter. Income was not found to be significant in any of the reviewed studies.

Finally, there is the question of what information from the route choice process is fed into mode and destination choice models. Usually, such information reflects the average characteristics (or minimum path) between zone pairs. Halldórsdóttir (2015) suggests that models can be improved by using the logsums from route choice models as inputs into mode and destination choice models. Similarly, the author recommends adding relevant variables found in route choice models into the utility function of mode and destination choice models.

Our review included two studies that looked specifically at travelers' choice of walk and bicycling routes jointly with mode choices (Broach 2016; Mortini et al. 2017). Both studies provide valuable information on how travelers choosing to walk or cycle value different factors.

Table 2-1: Pros and cons of different route choice set generation methods

(Source: Li (2017))

Route Set Generation Type	Route Set Generation Methods	Description	Benefits	Limitations	References Examples
Stochastic	-	The costs of links follows probability functions like normal distribution or truncated normal Distribution	Efficient; Easy implemented	Large overlapping; Unreasonable routes	Bierlaire and Frejinger (2008)
Deterministic	Route Labeling	Minimizing or maximizing the generalized cost by scenario	Reasonable routes;	Need multiple labels;	Howard and Burns (2001)
	Link Penalty	Involved a penalty factor for existed links to avoid duplicated selection	Avoid overlapping	No reasonable meaning of routes; Penalty factor is hard to define	LIM and KIM (2005)
	Link Elimination	Delete the existed links following roles to avoid overlapping	Avoid overlapping; Increase the efficiency	Miss some links; No reasonable meaning of routes; Rule of deletion is hard to define	Rieser-Schüssler, et al. (2010)
	K-Shortest Path	Generating k-shortest path by various algorithms	Generate multiple routes by one scenario	Large overlapping; Hard to meet the required number of alternatives	Menghini, et al. (2009)

Key factors influencing the decision to walk or cycle

A key value of the literature review is information on explanatory variables that have been tested using advanced modeling techniques and found to influence traveler's decisions to walk or cycle. These are summarized in Table 2.2 and discussed below.

In our review, we have seen examples of using land-use and built environment, accessibility and infrastructure/network variables as well as traveler characteristics to explain walk and bicycle mode choices (Khan et al., 2014), walk and cycle route choices and mode choices including walk and cycle more broadly (Broach 2016), walk mode and destination choices (Clifton et al, 2016). Broach (2016) incorporates more detail on the quality of the network infrastructure, including variables describing the quality of the infrastructure and the amount of traffic.

We find some evidence that models developed from RP data return lower values than those derived from SP data (Li 2017 reporting work from Yang and Mesbah 2013).

Some of the models have included other variables not included in this list, including whether the trip was made on the weekend and the complexity of the tour, whereas the complexity of the tour increases the propensity to cycle decreases (Broach 2016).

We have not seen much evidence in our review of modeling work that incorporates other natural environmental factors, such as climate, extremes of temperature, precipitation, darkness or topography. One exception is Mahmoud et al. (2015) who tested and found that temperature impacted on demand for bicycling (in Canada). Munoz et al. (2016) also report a positive influence of summer and negative influence of rain and wind on bicycling.

Finally, the propensity to walk or cycle depends strongly on the journey purpose. As reported in NCHRP Report 770, the most common purpose for walking or biking in the US is for 'other social/recreational' travel, which accounts for almost half (47.3%) of bike trips and 35.4% of walk trips. After Other Social/Recreational travel, the most frequent purposes for walking are Other Family / Personal Business (21.5%), Shopping (14.7%), Visiting Friends and Relatives (8.7%) and School/Religious purposes (8.6%). Travel to /from work accounts for only 4.5% of all walk trips. The most popular trips for biking after Other Social / Recreational travel are Visiting Friends and Relatives (9.8%), Other Family / Personal Business (8.2%) and School/Religious purposes (6%). Thus, purpose segmentation is an important component of modeling for walking and bicycling journeys.

Two variables listed in Table 2.2 that are consistently found as important variables in walk and bike mode choice models, both in research and practice, are car ownership and age. People in households with no cars are more likely to walk or bike, as are people in households own fewer cars than drivers.

In the US, the propensity to choose the walk or bike mode becomes lower with age once people reach age 55 or so. Age-related variables are typically stronger for the bike more than for the walk mode. For longer-term forecasting models, however, it may be important to consider age-cohort effects as well, since the current age-related differences in walking and biking behavior may not persist to the same degree into the future. RSG (2019) estimated a mode choice model for adult non-work trips, pooling the data from the last four National Household Travel Survey (NHTS) survey samples from 1995, 2001, 2009 and 2017. Using longitudinal data, it is possible to separate out true age effects (how old the respondent was at the time of the survey) from age-cohort effects (what year the respondent was born).

As seen if Figure 2.1, the utility coefficients for the walk and bike modes (relative to auto) become increasingly negative with age, with the variable for the age 45-54 group constrained to 0 as the base group. The age-related differences are stronger for bike than for walk. After age effects are accounted for, however, Figure 2.2 shows that each newer generation has a somewhat higher utility for the walk and bike modes (with those born 1955-64 used as the base group with coefficient constrained to 0). The age-cohort effects are even stronger than the age-related effects, particular for the bike mode across the oldest cohorts. It appears that both the walk mode

and the bike mode are becoming more attractive for the youngest age cohorts, with walk and bike having effects of a similar magnitude.

The results suggest that the decrease in walk and bike trips that one might expect in the future due to the steady shift of the US population toward older age groups will be counteracted to some extent by the trend that each new generation of senior citizens will bike and walk somewhat more than the generation before them.

Figure 2-1: **Age group variables for adult non-work trip mode choice, based on NHTS data from 1995-2017**

(Source: RSG, 2019)

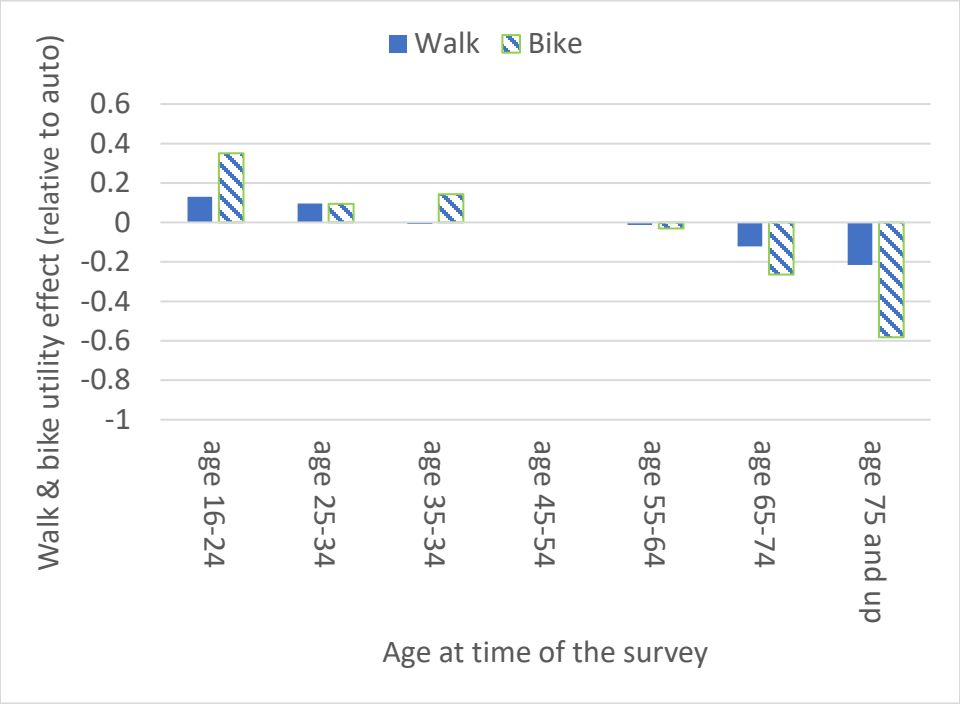


Figure 2-2: **Age-cohort variables for adult non-work trip mode choice, based on NHTS data from 1995-2017**

(Source: RSG, 2019)

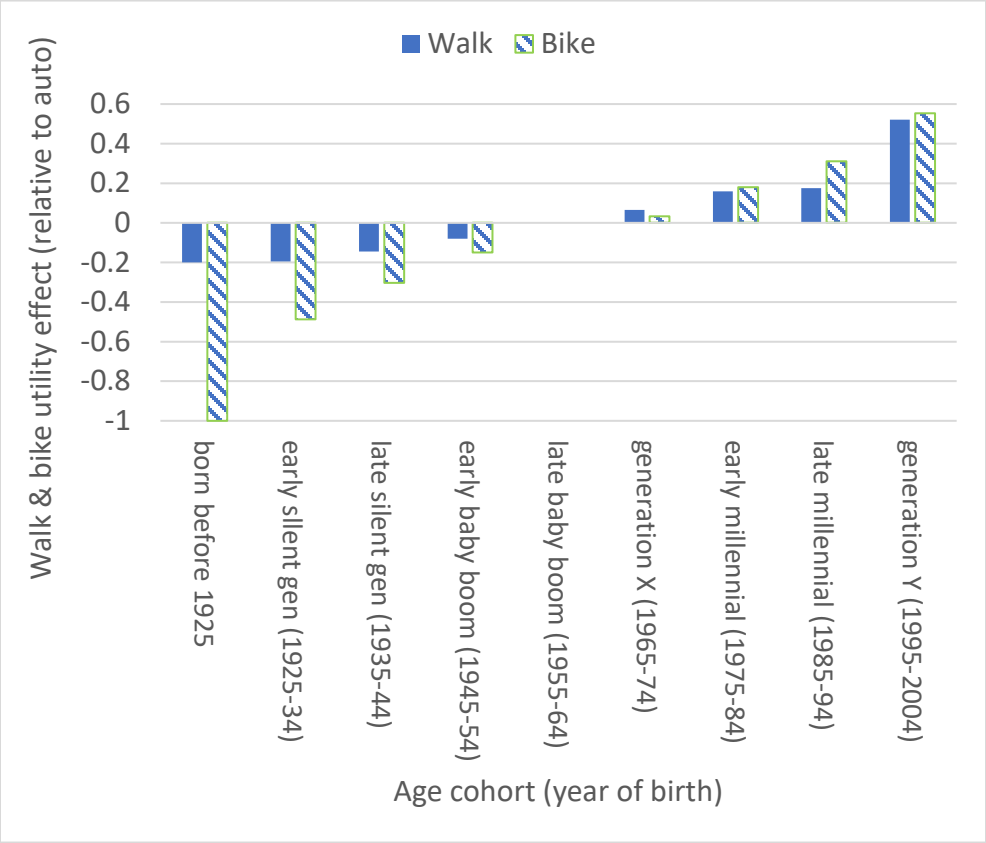


Table 2-2: Key factors influencing the decision to walk or cycle that have been incorporated in models

Traveler characteristics / Socio-economic variables	Infrastructure / network / facilities	Land-use variables
Age	Distance	Household / employment density
Gender	Travel times and costs (for other modes)	Mix of uses
Work/student status	Directness	Transit stop density / distance to the nearest transit stop
Income	Slope / gradient / hilliness	Accessibility, e.g. attractions of a given type within a given distance
Vehicle ownership / household competition for vehicles / car availability	Traffic volumes / lanes / speed / road type	Urban / suburban / rural areas
Driver license **holding**	Number / type of intersections	
Presence of children	Number of turns / left-turns (especially with heavy traffic)	
Household variables, including household size, workers, number of cars, competition for cars	Cycle / walk facilities / facility continuity, including cycleway network, parking and complementary infrastructure such as showers	
Education level	Parking on road (parallel or angle) /parking occupancy	

Attitudinal and Perceptual Variables

It may be important to include attitudinal indicators in models of cycle and walk demand for several reasons. The first is that the characteristics of the bicycle as a transport mode make it difficult to explain demand for bicycling with traditional variables like time and cost only and that attitudinal factors influencing bicycle choice may be the main determinants of demand rather than standard measures of level of services (Munzon et al. 2017). Second, it is hypothesized that promotional and educational campaigns can influence travelers' perceptions and attitudes to walking and bicycling and that these changes can influence the demand for these modes (Maldonado-Hinarejos et al. 2014).

Munzon et al. (2017) undertook a literature review on decisions to cycle for utilitarian purposes to summarize and assess the evolution in explanatory variables—including attitudinal variables—and analytical methodologies used. Fifty-four studies conducted from 1990 were identified and examined, from transport planning, travel behavior and health science. They note the presence of socio-economic and household characteristics, trip characteristics, the built and natural environment and bicycling facilities on bicycle demand, as well as several subjective variables that are incorporated in cycle models, including:

- Perceptual indicators of environmental and bicycling facilities, including perceptions of hilliness, weather and traffic risks, distance and bicycle facilities (network, parking, shower and ranks) are more common, with perceptions of noise, pollution, traffic flow, theft, conflict with pedestrians, neighborhood characteristics and proximity to services, streetlights and car facilities being less common.
- Psychological indicators, including satisfaction with bicycling, perceptions of comfort, convenience and awareness, positive social norm and support, high perceived behavioral control, non-commuting bicycling habits, being anticar or not having an interest in bicycling.

Both aggregate and disaggregate modeling approaches are incorporated in the review, although most use disaggregate modeling approaches (and few of the aggregate models incorporate psychological indicators or latent variables). They also note that most of the discrete choice models were derived from SP data, although some use both RP and SP data.

Further, most of the studies focus on bicycle commuting trips.

In general, psychological factors like perceptions and attitudes are modeled as latent variables, which cannot be measured by the researcher and are inferred from other variables called indicators.

Munzon et al. (2017) identify three methods of incorporating perceptions and latent variables in discrete choice models: (i) incorporating psychological indicators directly into the utility equation, (ii) sequential estimation, where psychological indicators are included in the utility function using a sequential estimation procedure of first estimating latent variables and then incorporating these in choice models (Maldonado-Hinarejos et al. (2014)—discussed in further detail below—is an example), and (iii) simultaneous approaches, where hybrid choice models incorporating latent variables are estimated simultaneously (referred to in the literature as the

integrated choice latent variable [ICLV] model). They note two disadvantages of the sequential modeling approach, specifically that the resulting explanatory variable estimates may biased and inconsistent.

They note that there is no "uniform methodology" for identifying relevant factors, noting (Munzon et al. 2017):

"The HCM (hybrid choice modelling) literature generally focuses on deriving estimators with good statistical and computational properties (due to the complex formulation of the likelihood function), but with little description of how the latent variables are actually hypothesized, constructed, and validated, and with the set of indicators for the latent constructs usually shown as ad-hoc measurement scales. This lack of a uniform methodology makes it difficult to compare studies and creates limitations in identifying the potential evolution of changing attitudes."

Based on their review they identify the most common psychological latent variables, summarized in Table 2.3 below. The list of indicators is intended to identify the most common psychological latent variables reviewed in terms of safety, comfort, convenience, awareness, social norm and bicycle ability, and is a compromise between an extensive list identified from the literature and a practice list for inclusion in a municipal household travel survey. Munzon et al. (2017) argue that the consistent use of indicators as the ones they propose should facilitate inference, especially if implemented in longitudinal and before-and-after studies.

Munzon et al. (2017) also make several comments on future research. First, they recommend that future research focus on development of market segmentation approaches—using structural equation modeling and hybrid ICLV approaches—to improve policies and programs to encourage bicycling. Second, they note that forecasting processes are "notably absent" from ICLV approaches and that "latent constructs appear to be key to a better understanding of current motivations for bicycle choice, but the use of weak structural relationships is weak forecast power." Again, they recommend that structural equation models are necessary to improve the forecasting power of models with latent variables. Attitudinal change models would also be needed to represent and forecast future bicycle adoption levels under different policy scenarios.

Table 2-3: Key indicators to identify bicycle latent variables

(Source: Munzon et al. 2017)

Degree of agreement or disagreement towards: bicycle use for urban mobility is….	
Accident risky (S)	Time reliable (C)
Theft risky (S)	Flexible (C)
Conflicts with pedestrians (S)	Independent (C)
Weather dependent (CM)	Relaxing and fun (C)
Sweat (CM)	Environmentally friendly (A)
Traffic stressful (CM)	Healthy (A)
Quick (C)	Cheap (A)
Degree of limitation provoked by…	
Ride in traffic (F)	Hilliness (PBC)
No cycleways (F)	Maneuvering (PBC)
No safe parking (F)	Physical condition (PBC)
No showers / ranks at destination (F)	Fix a puncture (PBC)
	Helmet use (PBC)
Considering your (possible) bicycle use for urban mobility:	
(1) to what extent (would) the following groups of people approve?	
(2) how important to you is the opinion of the following groups of people in this regard?	
My family (SN)	
My friends (SN)	
My co-workers or classmates (SN)	

Note: Expected latent variables in parentheses next to indicators: (S): Safety; (CM): Comfort; (C): Convenience; (A): Awareness; (F): Bicycle facilities; (PBC): Bicycle ability; (SN): Social norm.

In this same area, Maldonado-Hinarejos et al. (2014) develop hybrid discrete choice models of bicycling choice relative to other modes, that capture not only travel times, the travelers' socio-economic characteristics, such as age, but also include attitudes towards bicycling[2], perceptions of the image of bicycling and stress arising from safety concerns[3]. Based on literature review, they collected data to identify four latent variables identified in the literature: (i) probike, (ii) image, (iii) context and (iv) stress. The probike factor described environmental and sustainability attitudes. The second and third factors reflected the image of bicycling in terms of reliability and context regarding safety issues. The fourth reflected stress and cycle convenience. The effects of these variables were captured through 19 attitudinal and perceptual indicators (measured on a Likert scale from 1 to 5). Hybrid discrete choice models were derived from SP data exploring the effect of cycle lane provision, volume of traffic on the road, cycle parking and journey time—as well as latent attitudinal variables—on stated choice of cycle[4]. These models incorporated a

[2] Maldonado-Hinarejos et al. describe attitudes as latent variables corresponding to the characteristics of the decision maker reflecting their needs, values, tastes and capabilities (Daly et al. 2012) that are formed over time and are affected by experience and external factors including socio-economic characteristics (Ben-Akiva et al. 2002)

[3] Maldonado-Hinarejos et al. define perceptions as a measure of the individual's cognitive capacity to represent and evaluate the levels of attributes of different alternatives.

[4] A sequential estimation method was used, with the shortcomings noted earlier.

random term for travel time, the three attributes from the SP exercise, four demographic characteristics (age, gender, ethnicity and residential area) and the four latent variables described above. The latent variables improved the fit of the model significantly – and in fact the latent variables, the cycle time and socio-economic terms are the only significant explanatory variables of cycle choice (the parameters for cycle lanes and traffic flow were not statistically significant in the models). The resulting model was then used to evaluate the effect of three scenarios: (a) an improvement in attitudes (by one scale point), (b) improved cycle parking facilities and (c) both improvements in attitudes and improved cycle parking facilities. Improvements in attitudes lead to a similar level of increase in bicycling as parking facility enhancements, although the authors note that one of the shortcomings of the impact analysis is that it is not clear what policies may lead to a one scale point improvement in attitudes.

Wardman et al (2007) describe the development of a mode choice model from a combination of SP and RP data. The model specification for cycle included a detailed representation of cycle network conditions, with five levels represented, socio-economic effects such as age and income, provision of cycle facilities, perceptions of danger and bicycling ability, and the proportions of the population and colleagues who cycle. The model was used to test scenarios with improvements to the cycle network and the provision of bicycling facilities.

CHAPTER 3. RESULTS OF THE SURVEY ON MPO/DOT PRACTICE IN MODELING WALK AND BIKE TRIPS

3(A) INTRODUCTION

This chapter summarizes the responses to a survey of MPO and DOT modeling staff regarding their current and planned practice in modeling pedestrian and bicycle demand as part of NCHRP Project 8-36c, Task 141. The survey was drafted in Word, as shown in Technical Appendix B. After incorporating comments from the NHCRP project panel, the questionnaire was programmed in Survey Monkey Gold to administer it on-line.

Invitations to the survey were sent out via email in January of 2018 by the Association of Metropolitan Planning Associations (AMPO) and the National Association of Regional Councils (NARC) to their MPO members—roughly 400 MPOs in total. A general invitation to MPO and DOT modelers was also sent out via the Federal Highway Administration (FHWA) Travel Model Improvement Program (TMIP) email forum in February. The initial response from State DOT representatives was relatively low, so 25 additional invitations were sent by email in May to select DOT modelers known to project team members. (Just over half of those 25 responded.)

In total 101 respondents completed the entire survey. Of these, 72 are from MPOs, 24 from state DOTs, and 5 from other types of agencies (3 from county agencies, 1 from a city agency, and 1 from the Federal government). There were only two cases identified (one MPO and one DOT) where two people from the same organization responded. The 96 completed surveys from MPO and DOT representatives were analyzed, and the key results are reported in the following sections.

The survey data was analyzed in detail, using several different ways of segmenting the respondents, including by MPOs as opposed to DOTs, agencies that currently model bicycling and walking trips as opposed to those that do not, and agencies according to the their current use of an ABM and their interest in using such a model in the future. A summary of the analysis results is provided in this chapter, while Technical Appendix B provides a more complete listing of the tabulations done on the survey responses.

The sections below provide a summary and highlights from the analysis of survey responses. We emphasize that the findings reported here only represent those who chose to respond to the survey, and not all MPOs and DOTs in the US. As the following sections indicate, the responses are likely to over-represent agencies with greater interest and resources for modeling bicycle and pedestrian trips.

3(B) OVERVIEW OF THE RESPONDING AGENCIES

The survey asked several questions about the respondent's agency, to classify the agency by state/region size, staff size, and walk and bike share. The response categories differed for DOT versus MPO respondents.

Responses were obtained from 24 state DOTs. Table 3.1 shows that almost half of the DOT respondents estimated their state's population is over 8 million, while only 24% of the 50 states

have a population that high. This difference indicates the DOT sample is skewed toward the larger states. It also appears to be skewed away from the smallest states, those with less than 1.5 million residents (4% of DOT respondents vs. 22% of the 50 states).

Table 3-1: DOT respondents by state population, compared to actual distribution of the 50 states

State DOT's only- What is the population of your state?	Survey	Actual
Less than 1.5 million	4%	22%
1.5 million to 3.5 million	29%	20%
3.5 million to 5.5 million	8%	14%
5.5 million to 8 million	13%	20%
Over 8 million	46%	24%

MPOs are not defined uniformly by state, county, Census, or metropolitan boundaries, so it is more difficult to compare the survey responses to actual data. Table 3.2 shows the survey response distribution of region population, compared to the distributions for metropolitan statistical areas MSAs and for combined statistical areas (CSAs), as defined by the Census Bureau. The United States has 383 MSAs and 171 CSAs (which can comprise multiple MSAs), compared to 408 MPOs as of 2015. Most MPOs are similar in size to MSAs, although some of the largest ones are similar to CSAs or even larger. Regardless, the MPO survey sample is skewed toward the larger regions, those with over 2.5 million residents, and away from the smallest regions, those with less than 250,000 residents.

Table 3-2: MPO respondents by regional population, compared to actual distributions for MSAs and CSAs

MPO's only- What is the population of your region?	Survey	Actual MSA's	Actual CSA's
Less than 250,000	30%	51%	29%
250,000 to 500,000	19%	21%	18%
500,000 to 1 million	19%	14%	20%
1 million to 2.5 million	11%	8%	19%
2.5 million to 5 million	11%	4%	7%
Over 5 million	10%	2%	7%

That the largest states and regions are over-represented in the MPO and DOT survey samples is to be expected, as walking and biking tend to be of more policy interest in the more urbanized regions, and the larger agencies typically have more staff and budget to model pedestrian and bike demand, so will tend to be more interested in the survey topic.

DOT and MPO respondents were asked their state/region's bike and walk mode shares for commuting. Table 3.3 shows 30% of DOT respondents stated they did not know their state's bike mode share. Of those that did provide an estimate, the responses are fairly consistent with the actual commute bike-share distribution across states from the American Community Survey (ACS), as reported in the "Alliance for Walking and Biking 2016 Benchmarking Report."

For state-level walk mode share (Table 3.4), of the 70% who gave an estimate, most stated a commute walk mode share of less than 1%, while, according to the report cited above, all states have a commute walk mode share of above 1%. However, walk and bike mode shares for entire states are not cited as often as those for individual cities or metropolitan areas, so the values may be less familiar to agency staff.

Table 3-3: Estimated bike more share for commuting for DOTs

State DOT's only- What is the state's bike mode share for commuting?	Survey	Actual
0-0.5%	43%	46%
0.5-1%	17%	36%
1% or greater	9%	18%
Don't know	30%	

Table 3-4: Estimated walk share for commuting for DOTs

State DOT's only- What is the state's walk mode share for commuting?	Survey	Actual
0-1%	39%	0%
1-3%	17%	56%
3% or greater	13%	44%
Don't know	30%	

Table 3-5: Estimated bike share for commuting for MPOs

MPO's only- What is the region's bike mode share for commuting?	Survey-Under 1 mil pop.	Survey-Over 1 mil pop.	Actual-50 largest cities
0-1%	45%	48%	62%
1-3%	28%	35%	26%
3% or greater	8%	13%	12%
Don't know	19%	4%	

Table 3-6: Estimated walk share for commuting for MPOs

MPO's only- What is the region's walk mode share for commuting?	Survey-Under 1 mil pop.	Survey-Over 1 mil pop.	Actual-50 largest cities
0-1%	15%	17%	0%
1-4%	47%	71%	68%
4% or greater	17%	18%	32%
Don't know	21%	4%	

Answers to analogous questions for MPO respondents are shown in Tables 3.5 and 3.6, with the MPOs split out between regions with greater than and less than 1 million population. No published mode shares exist across MPOs, so the "actual" values for comparison are for the 50 largest US cities, again from ACS data compiled by the Alliance for Walking and Biking (2016). Almost all the MPO respondents from the larger regions (over 1 million residents) could provide an estimate, and those estimates match the distributions from the 50 largest cities fairly well. Some skew exists toward lower walk mode shares compared to the city data, but this may be because the MPO regions typically also include more rural areas outside of the main cities.

3(C) SUMMARY OF THE SURVEY RESPONSES

Sixty (60%) of the responding MPOs and 25% of the responding DOTs currently model bicycle and pedestrian demand, in most cases as two separate modes. Few cases (3 of the MPO respondents) model bicycle demand but not pedestrian demand, and no cases model pedestrian demand but not bicycle demand.

Table 3-7: Does your agency currently use a model to study/forecast bicycle and pedestrian trip demand in your region?

	Regional MPO	State DOT
Yes, both bicycle and pedestrian trip demand, as separate modes	34.7%	16.7%
Yes, bicycle and pedestrian trip demand, grouped as a single "non-motorized" mode	19.4%	8.3%
Yes, bicycle trip demand, but not pedestrian trip demand	4.2%	
No, neither	41.7%	75.0%
Total	100.0%	100.0%

As the sample is skewed toward larger states and regions, and probably also skewed toward agencies with more interest in the subject matter, the percentage of survey respondents who currently model bike and walk trips is likely higher than the actual percentage across all MPOs and DOTs. Nevertheless, about 50% of all survey respondents do not current model walk and bike trips, which provides a good basis to compare the agencies that have such models to those that do not. The following are some key contrasts found from further analysis (with a full tabulation of results provided in Technical Appendix B).

All of the MPOs with five or more modeling staff model bike and walk trips. The large majority of MPOs with three or four modeling staff model bike and walk trips, while the majority of those with fewer than three modelers do not.

- All of the DOTs with 10 or more modeling staff model bike and walk trips, while most of those with fewer than 10 modelers do not. (DOTs typically maintain statewide travel models, with a focus on longer-distance trips, so adding the capability to model walk and bike trips represents a larger challenge for DOTs in general, as compared to MPOs that maintain regional-level models.)

- Almost all of the DOTs in states with a population of more than 5.5 million model bike and walk trips, while the majority of DOTs in states with a population of less than 5.5 million do not.
- All of the MPOs in regions with over 5 million residents model bike and walk trips, as do the majority of MPOs in all size categories above 250,000. Most of the MPOs in regions smaller than 250,000 residents do not.

The respondents who indicated their agency currently models bike and walk trips were asked to list the agency's motivations for doing so. Table 3.8 shows that nearly all of the MPOs with current models use them for regional program evaluation. None of the other motivations was mentioned by a majority of the MPOs that model bike and walk trips, although it is interesting that health benefits and social equity are mentioned nearly as often as local program evaluation.

Table 3-8: What is/are your agency's motivation(s) for modeling bicycle and/or pedestrian trip demand?

(multiple answers allowed)	Regional MPO	State DOT
Modeling for regional program evaluation	53%	13%
Modeling for local program evaluation	24%	4%
Modeling for traffic safety evaluation	8%	4%
Modeling for active transportation health benefit evaluation	21%	4%
Modeling for social equity evaluation	19%	4%
Other reasons	7%	13%
Do not model bike/ped demand	42%	75%

About half of the DOT respondents with current bike/walk models mentioned regional program evaluation, while about half mentioned other reasons. The most common "other" reason mentioned is that mode choice models are needed to obtain accurate estimates of auto trips, net of transit and non-motorized modes.

Respondents were also asked about the types of bicycle modeling approaches and data tools they currently use or are interested in adopting. In the tables below, responses "Currently use," "Currently developing for future use," and "Plan to develop in the next 1-2 years" are grouped in the columns "Currently use." (The more detailed breakouts are available in the workbook.)

Table 3.9 shows the breakdown in terms of bike modeling approaches. The number of agencies using activity-based or tour-based models is similar to the number using trip-based models, with relatively few using direct demand models. In many cases, agencies that do not currently have a model are interested in developing a trip-based model, while agencies that currently have a trip-based model are interested in adopting an activity-based or tour-based model. Relatively few agencies use findings from a bicycle route choice model, although over 40% of MPO respondents are interested in doing so. Almost a quarter of responding MPOs currently assign bicycle trips to a network, while over half are interested in doing so in the future. Over 60% of MPOs and 50% of DOTs are interested in modeling bike access to transit, although few do so currently.

Table 3-9: Which bicycle modeling approaches do you currently use or are interested in adopting?

	Regional MPO	Regional MPO	State DOT	State DOT
	Currently use	Interested in	Currently use	Interested in
Bicycle trips predicted from an activity-based or tour-based model	27%	33%	26%	13%
Bicycle trips predicted from a trip-based model	33%	32%	17%	35%
Bicycle trips predicted from a bicycle-specific direct demand model	11%	34%	0%	30%
Transferring findings from bicyclist route choice models	11%	41%	4%	13%
Assigning bicycle trips to a network	23%	53%	13%	30%
Modeling bicycle access to transit	11%	63%	5%	50%

Table 3.10 shows the breakdown for the analogous question (Question 4) for modeling walk trips. For most of the types of modeling, the frequency of answers is similar to that for modeling bike trips (Table 3.9). That is not surprising, since most agencies currently use the same model to predict both walk and bike trips, and agencies who are interested in adopting new models would tend to use them for both walk and bike trips.

One noticeable difference is for route choice models. Only 2% of MPO respondents and no DOT respondents currently use findings from pedestrian route choice models, although 40% of MPO respondents and 20% of DOT respondents would be interested in doing so. Fewer respondents assign walk trips to a network, although over 40% of MPO respondents and 25% of DOT respondents would be interested in doing so. Compared to bike access to transit, more MPO respondents currently model walk access to transit in detail, and most of those who do not would be interested in doing so in the future.

Table 3-10: Which pedestrian modeling approaches do you currently use or are interested in adopting?

	Regional MPO	**Regional MPO**	**State DOT**	**State DOT**
	Currently use	**Interested in**	**Currently use**	**Interested in**
Walk trips predicted from an activity-based or tour-based model	28%	27%	26%	13%
Walk trips predicted from a trip-based model	40%	24%	22%	22%
Walk trips predicted from a bike-specific direct demand model	14%	29%	0%	30%
Transferring findings from pedestrian route choice models	2%	39%	0%	22%
Assigning walk trips to a network	12%	41%	9%	26%
Detailed modeling of transit walk access and egress	37%	40%	4%	50%

A more detailed analysis, based on the tabulations provide in Technical Appendix B, shed some more light on the differences between agencies that have current or planned activity-based or tour-based models (ABM) incorporating walk or bike, those who are interested in such a model, and those who have no plan or interest. Some key differences are:

- Two-thirds of the responding DOTs with fewer than three modeling staff have no plan or interest for an ABM, while most agencies with three or more staff either have a current ABM or are interested in one.
- None of the DOT respondents in states with less than 1.5 million population are interested in adopting an ABM, and only 29% of DOT respondents in states with 1.5-3.5 million are interested. The majority of DOT respondents in states with more than 3.5 million residents either use an ABM or are interested in doing so.
- Responding MPOs in regions with over 1 million residents mostly have a current or planned ABM (about 65%), with another 25% interested. In contrast, only about 10% of

responding MPOs in regions with under 1 million residents have a current or planned ABM, and only about half of those that do not are interested.

- Ninety percent (90%) of the responding MPOs with five or more modeling staff have a current or planned ABM, and the other 10% are interested. For responding MPOs with three or four modeling staff, the split is 60% current/40% interested. For responding MPOs with only one or two modeling staff, the majority have no plan or interest.

From the points listed above, modeling staff size appears to be a major factor in decisions on what types of methods to use (if any)—a finding that is confirmed by the answers to survey questions discussed later in this section. It is likely that staff size is related to the size of the region or state, but also reflects the organization's budget allocation towards modeling and commitment to modeling in general.

Table 3.11 shows the breakdown of responses asking about data sources for modeling bicycle trips, using the same "currently use" and "interested in" categories as Tables 3.9 and 3.10. Bicycle count data is the type of data most used by both MPO respondents (70%) and DOT respondents (20%). (It was not asked if bicycle count data is mainly collected together with auto count data or as part of a separate effort. This is a question that was asked in follow-up interviews.) All of the other data types are used by 20% to 30% of both MPO and DOT respondents, except bicycle trip intercept/OD data, which is used by only 13% of DOT respondents. Although OD/intercept survey data has the lowest current use, it has a high rate of potential interest—over 40% for both MPOs and DOTs. GPS data also has fairly high current use (over 25%) and interest (47% for MPOs). GPS data are obtainable in various ways, including disaggregate GPS surveys of bicycles only, smartphone-based surveys of all household travel, or passive "big data" (which is typically not broken out by mode).

Table 3.12 has the responses for the analogous question for pedestrian data sources. Again, count data is the most commonly used type of data, although it is used less commonly than for walk trips than for bike trips. In fact, the "currently use" percentages are somewhat lower for pedestrian data than for bike data for all of the data types for both MPO and DOT respondents. The type that is most similar between the modes is the use of an all-streets network, since in that case the same network can be used for both walk and bike trips. The level of interest in using data types that are not currently used is just as high (or higher) for walk trips as for bike trips. In particular, the majority of MPO respondents that are not currently using pedestrian count data are interested in having such data.

Table 3-11: Which bicycle data sources do you currently use or are interested in using?

	Regional MPO	Regional MPO	State DOT	State DOT
	Currently use	Interested in	Currently use	Interested in
Collection/use of bicycle count data	70%	20%	50%	21%
Collection/use of bicyclist intercept/O-D survey data	21%	42%	13%	44%
Collection/use of GPS data specific to bicycle trips	26%	47%	29%	33%
Use of an all-streets network	31%	28%	30%	17%
Use of OpenStreetMap data and/or tools	21%	21%	26%	22%
Use of microzone-level detail (e.g. census blocks or parcels) in model	28%	25%	29%	25%

Table 3-12: Which pedestrian data sources do you currently use or are interested in using?

	Regional MPO	Regional MPO	State DOT	State DOT
	Currently use	Interested in	Currently use	Interested in
Collection/use of pedestrian count data	47%	35%	35%	30%
Collection/use of pedestrian intercept/O-D survey data	18%	43%	9%	39%
Collection/use of GPS data specific to pedestrian trips	21%	40%	21%	22%
Use of an all-streets network	30%	26%	26%	35%
Use of OpenStreetMap data and/or tools	16%	26%	17%	26%
Use of microzone-level detail (e.g. census blocks or parcels) in model	23%	29%	29%	25%

Respondents were also asked "Are there any bicycle or pedestrian modeling tools or approaches that your agency is using that were not listed in the preceding questions?." 10% of MPO respondents and 8% of DOT respondents answered yes and provided more details. Most provide more clarification on the type of count data collected or how the data is used in modeling—mainly around defining specific types of walk/bike accessibility measures. One type of data mentioned that was not listed in the survey question is the number of times that pedestrian-activated signals are activated at specific intersections.

Respondents were also asked about the importance of various possible types of impediments for modeling bicycle or walk trips. The percentage of MPO and DOT respondents who said that each type of impediment was "very important" or "somewhat important" is shown in Table 3.13. As hinted at in the discussion above, staff time and funding for staff or consultant time are seen as the biggest impediments, with about 90% of MPO and DOT respondents rating those as either very or somewhat important. Funding for data collection/acquisition shows a similar level of importance around 90%. Level of staff training is also mentioned as important by about 70% of

respondents, with lack of modeling guidance and lack of training courses mentioned as important by about 60% of MPO respondents and 50% of DOT respondents.

Lack of agency consensus appears as the least important of the possible impediments asked about, although about 40% of respondents rated it as very or somewhat important.

Table 3-13: How important are the following issues as impediments to your agency's development of tools or approaches for modeling bicycle and/or pedestrian demand?

	Regional MPO	Regional MPO	State DOT	State DOT
	Very important	Somewhat important	Very important	Somewhat important
Availability of staff time	66%	29%	50%	38%
Level of staff training	40%	30%	33%	38%
Funding for staff and/or consultant time	59%	26%	42%	42%
Funding for computing resources	28%	25%	21%	25%
Funding for data collection and/or acquisition	58%	35%	42%	46%
Lack of agency consensus on modeling/research priorities	13%	27%	25%	17%
Lack of clear guidance from the modeling/research community	20%	38%	21%	29%
Lack of training courses directly related to modeling bike/ped demand	24%	35%	13%	42%

Finally, almost 20% of respondents described other impediments that were not provided in the survey list. The two main categories that most of the open-ended responses fall into are (a) a lack of access to good/sufficient data, and (b) a lack or priority given to bicycle and pedestrian demand compared to other modes—particularly when the modeling is dictated by a larger entity such as a state DOT.

3(D) IN-DEPTH FOLLOW-UP INTERVIEWS

The on-line survey also asked respondents if they would be willing to participate in a follow-up interview. Twelve respondents who indicated they would be willing to do so were re-contacted by email and invited to participate in a telephone interview at a convenient time. All 12 invitees accepted and were interviewed in late August 2018.

The interviewees were selected to include both MPO and DOT respondents from various regions of the US, and to include agencies that currently use activity-based (ABM) or tour-based models, agencies that currently use trip-based models, and agencies that currently do not model walk and bike trips. The respondents also covered a range of state and region population sizes.

Table 3.14 summarizes the selected agencies. They include eight MPO and four DOT representatives from a range of sizes of regions and states. Four agencies use advanced activity-based models with separate walk and bike modes, four use a trip-based model with a combined walk and bike non-motorized mode, and four do not currently model bike and pedestrian trips explicitly. All three of those groups included both MPO and DOT interviewees.

The interviews were done to obtain further detail and insight behind the answers provided to the on-line questionnaire. The questions asked in the interviews were varied somewhat depending on the situation and priorities of each agency, but generally included:

- Asking more detailed questions about their modeling methods and future modeling plans.
- Asking more detailed questions about their current data availability and future data collection plans.
- Asking how the local state, regional, and local agencies and advocacy groups interact, particularly for determining bicycle and pedestrian project funding and priorities and policies.
- Asking how bicycle and pedestrian models and data are used (or not used) in various types of local, regional, and state planning decisions.
- Asking what future changes in bicycle and pedestrian modeling, planning, or policies are anticipated.
- Asking about any impediments to modeling bike and walk trip demand.
- Asking how the current NCHRP project could be of most use to the agency and its staff.

Table 3-14: Details of follow-up interviews

Agency Type / Region of the US	Current Model Status	Size of Region / State
MPO in the Southeast	Use ABM, walk and bike trips separate	Very large (over 5 million)
MPO in the Northwest	Use ABM, walk and bike trips separate	Large (2.5 to 5 million)
MPO in the Northeast	Use trip-based model, walk and bike combined	Medium (0.5 to 1 million)
DOT in the Mountain West	Use ABM, walk and bike trips separate	Medium state (3.5-5.5 mil.)
MPO in the Midwest	Use ABM, walk and bike trips separate	Large (2.5 to 5 million)
MPO in New England	Use trip-based model, walk and bike combined	Small (less than 250,000)
MPO in the East mid-Atlantic	Use trip-based model, walk and bike combined	Very large (over 5 million)
DOT in the South	No current bike/ped model	Small-medium (1.5-3.5 mil)
MPO in the Northeast	No current bike/ped model	Small (less than 250,000)

Agency Type / Region of the US	**Current Model Status**	**Size of Region / State**
DOT in the Midwest	Use trip-based model, walk and bike combined	Small-medium (1.5-3.5 mil)
MPO in the Pacific states	No current bike/ped model	Medium (0.5 to 1 million)
DOT in the Southeast	No current bike/ped model	Large state (5.5 to 8 million)

For the last question above, almost all agencies responded that they would like to read details of specific examples of "best practice" in bicycle and pedestrian modeling that are used around the country. Agencies were interested in learning more about the options for adding detail and their strengths and weaknesses. They were especially interested in understanding how similarly-sized areas and those with similar amounts of non-motorized travel handle modeling of these activities. Some participants expressed interest in tools that could be used in lieu of adding nonmotorized activity to their vehicle models, and they also expressed interest in having seminars, training, and literature focused around different levels of complexity, to more easily gauge which information would be most applicable to their situations.

Several agencies also mentioned the issue that current data may not be useful for modeling potential bicycle and pedestrian demand in regions where there is low current demand and a lack of dedicated infrastructure. Thus, the potential for transferring methods and models from regions with more infrastructure investment and more established bicycle pedestrian demand is another topic of apparent interest.

Rather than providing a separate summary of each interview, the interview responses will be used in two ways in the following chapters. First, any consensus of findings of the interviews will be used in the next chapter to aid in synthesizing the information from the literature review, the on-line survey, and interview responses to identify key gaps between the state-of-the-art and the state-of-the-practice in modeling demand for nonmotorized travel. Second, examples drawn from the interviews will be used to highlight specific topics discussed in the remaining chapters.

CHAPTER 4. IMPORTANT GAPS BETWEEN THE STATE-OF-THE-ART AND THE STATE-OF-THE PRACTICE

4(A) INTRODUCTION

In this chapter, we briefly summarize the material from the on-line travel survey of MPO and DOT modelers (reported in detail in Chapter 3) and the literature review of state-of-the art methods for modeling bicycling and walking travel demand (Chapter 2). Then, we synthesize that material to identify key gaps between the current state-of-the-art and the state-of-the-practice. The remaining chapters of the report then provide examples and recommendations for how modeling practice can evolve towards using more state-of-the-art methods.

4(B) A SUMMARY OF THE SURVEY AND INTERVIEWS ON THE STATE-OF-THE-PRACTICE

An on-line survey was carried out, inviting modelers from the roughly 400 regions MPOs and 50 state DOTs in the US. Responses were obtained from 72 MPOs and 24 DOTs. The responses to the on-line survey showed that just over half of the MPOs that responded to our survey model both bicycling and walking trips, while only about 25% of DOTs model bicycling and walking trips. For both MPOs and DOTs who model bike and walk trips, about two-thirds of the agencies model them as separate modes, while the other third model them as a combined “non-motorized mode”. It is important to keep in mind that the survey respondents are skewed toward the larger states and metropolitan regions that are more likely to have the interest and the resources to forecast walk and bike travel. All of the MPOs and DOTs with large modeling staffs model walk and bike trips, while the majority of agencies with fewer than three modelers do not. Thus, if we had obtained a 100% sample including all smaller regions and states, it would likely show that fewer than half of all MPOs and DOTs in the US model bicycle and pedestrian trip demand.

Both current practice and future interest in modeling nonmotorized travel are clearly more prevalent among MPO respondents than among DOT respondents. While most DOT respondents and interviewees indicated they are interested in bicycle and pedestrian travel issues and policies in their state, their statewide travel demand models often tend to be focused on longer trips—particularly auto trips on the state highways and other key roads. In cases where walk and bike trips are included in DOT statewide models, it is often so that they can be separated from auto trips, so as not to over-predict auto traffic. For MPO respondents, the strongest motivation for modeling nonmotorized trips is for regional program evaluation, although local program evaluation, evaluation of health benefits of active transportation, and social equity evaluation were also mentioned by almost half of the agencies that model bike and walk trips. MPOs who are not currently modeling walk or bike demand point to these same reasons as their motivation for wishing to model nonmotorized travel in the future.

Of the responding agencies that have models to predict nonmotorized trips, roughly half use a trip-based model, while most of the others use an activity-based (or tour-based) model. (Again we note that the survey sample is skewed toward larger regions and states who are more likely to use activity-based models.) The answers for modeling walk and bike trips are similar across the two modes, with two exceptions. First, most agencies who model nonmotorized trips model walk

access to transit in some detail, while few currently model bicycle access to transit (although most agencies are interested in doing so in the future). Second, the percentage of agencies who assign bicycle trips to a network is twice as high as the percentage who assign walk trips to a network, although the interest in doing so in the future is fairly high for both modes.

The current use and future interest in adopting advanced methods like ABM is strongly related to the size of the modeling staff. Of the responding MPOs with five or more modelers on staff, 90% have a current or planned ABM, and the other 10% are interested in developing one. Of the responding MPOs with only 1 or 2 modeling staff, the majority have no plan or interest to develop an ABM.

About 70% of responding MPOs collect bicycle count data, while just under 50% collect pedestrian count data. As was commented in some interviews and often found in practice, however, the amount of bicycle and pedestrian data collected is often meager in terms of the number of count locations and the length and frequency of count periods. This is particularly true when compared to the amount of count data available for cars and trucks. Several of the interviewees reported collecting additional bicycle and pedestrian counts as a necessary step toward modeling nonmotorized modes.

About 30% agencies currently use an all-streets network. About 20-25% currently use intercept/O-D survey data and GPS data for each mode. Most of those who do not currently use O-D or GPS data are interested in doing so in the future, although the interviews revealed that different modelers tend to have different concepts of what such data are exactly (or will be in the future), as well as different uses for the data.

About 25% of responding agencies said that they use microzone-level detail in their models. These tend to be the same agencies that use activity-based models, which better accommodate microzone-level detail.

For both MPOs and DOTs, the largest impediments to developing (improved) tools for modeling bicycle and pedestrian travel are the lack of availability of modeling staff time, as well as the lack of funding to hire more staff or consultants, and the lack of funding for more data collection and acquisition. Lack of clear guidance or training courses from the modeling/research community was mentioned as important or somewhat important by about half of the respondents, but not as important as the lack of staff and funding (which would be needed to take advantage of such guidance or training). These sentiments were echoed in the interviews. Funding and staff time are limited resources and adding model capability competes against many other demands. Interviewees were looking for clear guidance on appropriate next steps to advance their models, and, while this information was not seen as large of a barrier as the resource constraints, the knowledge gap limits staff ability to articulate the value of advancing their models.

Interviewees suggested some agencies had a lack of motivation to add nonmotorized modes. Some did not think that adding nonmotorized modes to their models, at least at the level they would likely pursue, would appropriately inform the questions they would ask. In these cases, agencies were more interested in pursuing tools that can be run as preprocessors or postprocessors in combination with existing models. There were also some agencies that felt the

level of nonmotorized travel was not significant enough to justify the effort to add to their models, or who worked in regions that did not want to dedicate resources to nonmotorized modes, when the major issues are related to automobile travel and reducing/avoiding congestion.

4(C) A SUMMARY OF LITERATURE ON THE STATE-OF-THE-ART

Many studies on modeling bicyclist and pedestrian choice behavior have been carried out and published in transportation journals, conference proceedings, and reports. The studies have focused on a range of choice contexts, including route choice, mode choice, destination choice, and tour or trip generation. The studies have relied on a variety of different types of data, including stated preferences in hypothetical choice situations and revealed preference data from actual choices; the latter from household travel surveys, project-specific custom surveys, or smartphone apps or other devices that provide GPS data. As is shown in Table 2.2, several key behavioral factors have been identified in those studies, falling into three main categories: (a) traveler characteristics. (b) infrastructure/network characteristics, and (c) surrounding land-use characteristics. Much of the published research is consistent as to the importance of specific variables in each of these categories.

One particular area of research focus has been on bicyclist route choice behavior. These studies and the resulting models tend to be technically complex, but, as we will describe in later chapters, such studies have produced useful results that have been implemented in a variety of ways in MPO models used in practice. Pedestrian route choice behavior has received less attention in both research and practice, but such research offers a similar potential for practical and useful results.

Another area of focus has been on attitudes and perceptions towards biking and walking—so-called “latent,” or “soft” variables. While such variables can be important, particular in regard to perceptions of safety and stress, it is challenging to obtain data on such variables that can be applied in practical modeling contexts.

4(D) KEY GAPS BETWEEN MODELING RESEARCH AND PRACTICE

While much of the published research uses advanced modeling techniques and innovative approaches, it is typically the case that the researchers do not have access to all of the data and experience that would be necessary to fully test their approaches in a practical modeling context such as an MPO regional travel forecasting study. Such practical studies typically require a good deal of auxiliary data such as zonal (and micro-zonal) land-use data, network-based zone-to-zone matrices of travel times and costs, detailed data on the regional population, and count data to validate the model results. So, in general terms, the gap is one that exists in most areas of travel behavior modeling—the need to bring promising new ideas and methods “out of the laboratory” and make them applicable within modeling tools that are accessible to MPO and DOT staff, their consultants, and, ideally, their constituent agencies such as county and city travel modelers. In the context of modeling walk and bike trip demand, there are particular gaps and challenges, described below. Because most of these gaps apply to the modeling of both walk and bike trips, the two modes are not treated in separate sections. However, it is noted when specific issues are more critical for modeling one of the two modes.

The need to accommodate greater spatial detail in practical models: Effective modeling of opportunities for walking and bicycling requires a greater level of spatial detail than the travel analysis zones (TAZs) used in most travel regional demand models. Compared to motorized travel, the trips tend to be shorter and more strongly influenced by the land use in the immediately surrounding area. Yet, the TAZ system is still required to allow modeling of motorized travel at the regional level, so the models must accommodate both levels of land-use and zonal detail. Fine level spatial detail in terms of land-use measures is particularly important for modeling walk trip demand, although the examples in the next chapter show that such detail is useful for modeling bike trip demand as well.

The need to use more network detail in practical models: Analogous to the point above, modeling walk and bike trips generally requires an all-streets network containing details on all local streets and details on bike lanes and bike paths of various types, pedestrian-only links (ideally including unpaved paths that are important shortcuts), and other key factors such steepness of grades and changes in elevation. It is rarely practical, to use such a detailed network for the entire region, however, so the model system must also accommodate multiple levels of network detail. In general, more network-level data is available for bicycle infrastructure (bike lanes and paths) than for pedestrian infrastructure (sidewalks, crosswalks, median islands, flashing beacons, etc.). Also, bike infrastructure can use a link-based spatial network structure that is similar to that used for road networks for autos, while pedestrian infrastructure is often more focused on intersections. Thus, it is more common in practice to use mode-specific network detail for the bike mode than for the walk mode, while more of a gap remains in practice for the treatment of pedestrian-related infrastructure and how that influences demand for walk trips.

The need to have methods that are accessible for different types of users, in combination with different types of existing models: Most of the commonly used ABM frameworks are already capable of accommodating multiple levels of spatial detail and network detail, in ways that are presented in the examples in Chapter 5. Trip-based models can also be adapted to use multiple levels of spatial and network detail through use of a two-stage approach. Examples are provided in the next chapter of both preprocessing and postprocessing approaches, where a module using more spatial and network detail to (better) predict walk or bike trips is run either before or after an aggregate trip-based model.

The need to relate demand modeling to bicycle and pedestrian performance measures that are used in other planning contexts: In addition to modelers, planners at various levels of Federal, state, regional, and local governments monitor and study accessibility by walking and biking, and they often maintain databases that are potentially useful for modeling. For example, Zhang, et al. (2014) describe an approach for creating and maintaining a database of pedestrian- and bicycle-related features of roads and intersections for the California DOT, using aerial photography and other methods. The Federal Highway Administration (FHWA) recently published a comprehensive guidebook for developing pedestrian and bicycle performance measures, including pedestrian space, road crossing opportunities, and even the presence of street tree canopies (Semier, et al. 2016). Such data could be used to develop richer measures of the attractiveness of walking and biking for use in modeling.

The need for methods to apply bicycle and pedestrian route choice models in practical ways: As mentioned above, route choice models can be quite complex to apply in their most rigorous form. Yet, the behavioral findings from these models can also be applied using simpler approaches, both to provide accessibility measures for mode choice models, and to assign bike or walk trips to networks.

The need to address perceptions regarding latent factors such as safety risk and health benefits: This is a challenge that has not been addressed to any great extent in practical forecasting models thus far. Although there are proxies for such factors, such as how separated Class 1 bike paths are preferred because they are safer and less stressful to use, there has not been a great deal of practical research to bring attitudinal variables into applied models. An example is the "safety in numbers" phenomenon. How might the perceived safety of bicycling improve as the number of bike trips on the streets and bike lanes increases? (For example, see Jacobsen, et al. (2015).)

The need for methods that are transferable from other regions: Some regions wish to model the availability of new types of bicycle or pedestrian infrastructure that currently do not exist within their region. As a result, there is no way to predict the behavioral outcome based on local data. If models of bicycle and pedestrian travel demand can be shown to be transferable across regions, then such regions can use models developed in other regions.

The need for accessible and transferable software tools: This is a general need within the travel demand modeling profession which amplifies the needs listed above. It is much easier to transfer methods or models developed elsewhere if there are software tools or modules designed with ease of use in mind. In addition to application software for trip-based and activity-based models, this need applies to network analysis tools to deal with bicycle and pedestrian facilities, as well as GIS-based tools to handle detailed land-use data to derive measures of accessibility and connectivity.

The need for more extensive data on observed walk and bike trips: There is a need for detailed travel survey data on walk and bike trips for estimating behavioral models, and also for passive "big data" and count data for walk and bike trips to calibrate and validate demand models. Issues regarding data availability are discussed in the next chapter in sections 5(G) and 5(H).

The emerging need to model new "micro-mobility" options such as bike share, electric bike (e-bike) share, and electric razor scooter (e-scooter) share: Modeling the demand for these emerging modes will require the same types of methods that are recommended for modeling walk and bike trip demand. Because these modes are so new and the demand is changing so fast in many places, a key challenge will be to collect and maintain up-to-date data on the use of these modes. Further discussion is provided in the Future Research section 6(D).

Several practical models and tools addressing the gaps listed above do exist. However, they are often not well-documented in the literature, given that the agency modelers and contractors who carry out the modeling projects do not have a great incentive to publish in journals. As a result, much of the documentation is in model documentation reports and memos that are often not

accessible in literature reviews. Much more work is presented at conferences, such as the various TRB conferences, and are available in the form of full papers or slide presentations. Some of the work that is published in these areas is more technical than interviewees find useful. Those that have the resources to attend one of the conferences find the presentations generally contain more actionable information. However, the smaller agencies are more likely to have fewer dedicated staff and have less resources to attend conferences. This results in the modelers with the least explicit training having the least access to actionable information, and they are not well positioned to leverage complex technical information typically found in journal articles.

Also, some modeling projects to advance the state-of-the-practice are currently ongoing and not yet documented for external audiences. The authors of this report have carried out some of these projects, and have studied the details of similar modeling projects carried out by others, Thus, the most useful aspect of this report will be provided in the next chapter—several examples of how the gaps identified above have been addressed to advance the current state-of-the-practice in modeling bicycle and pedestrian travel demand. In our in-depth interviews, several of the respondents indicated that they would find a focused discussion of such examples to be a useful product of this study.

CHAPTER 5. EXAMPLES OF RECENT ADVANCES IN BICYCLE AND PEDESTRIAN TRAVEL DEMAND MODELS USED IN PRACTICE

5(A) INTRODUCTION AND CONTEXT WITH RESPECT TO NCHRP REPORT 770

In this chapter, we provide descriptions and examples of several recent advances that have been applied to predict bicycle and pedestrian travel demand by regional, county, and state agencies in the US (plus one recent example from Europe). While most of the examples provided have been applied in the context of ABMs, some can be applied with trip-based models as well.

As this project is a follow-on from NCHRP Project 8-78, it may be useful to first put the examples that are provided below in the context of the methods recommended in that project, in NCHRP Report 770 (Kuzmyak, et. al 2014). Table 5.1 (which is, coincidentally, also Table 5.1 in Report 770) lists the various modeling approaches recommended in NCHRP Project 8-78.

The first "Tour Generation/Mode Split" approach included various detailed models that were created using much of the same data and methods that are applied in the Seattle Puget Sound Regional Council (PSRC) activity-based model. However, the models and methods were not described or applied in the context of a fully operational regional model system. In addition, some of the methods introduced have been further enhanced since the time of that report, and are discussed in detail in this chapter, in the context of activity-based model systems that are being used in practice.

The second "GIS-Accessibility Model" is an approach that was created for Project 8-78, using GIS processing of accessibility layers to look at the relative attractiveness of walk, bike, auto and transit for different trip purposes. This approach does not use travel networks explicitly, so is not suitable to be the main forecasting model for an MPO to predict traffic levels on specific routes and facilities. However, the approach may be a useful complement to network-based models, requiring less time and effort to use than a typical network-based forecasting model. A detailed description of the approach is available in NCHRP Report 770, so the approach is not treated in detail in this report.

The "Trip-Based Model Enhancements" performed on the Seattle/PSRC data are similar to some of the examples of possible enhancements to trip-based models described in this chapter, which we recommend using instead of the approach described in Report 770.

The "Pedestrian Demand Models" are useful modifications to enhance trip-based models. The Portland Pedestrian Model is described in this chapter as an example of preprocessor enhancement of a trip-based model used in practice.

"Bicycle Route Choice Models" (and findings from those models) have been implemented in a variety of ways in practice since NCHRP Report 770 was written, and several examples are provided in section 5(D).

Table 5-1: Summary of NCHRP 8-78 guidebook bicycle/pedestrian planning tools

(Source: NCHRP Report 770, Page 60).

Modeling Approach	Source	Characteristics
Tour Generation/ Mode Split	NCHRP 8-78 (Seattle/PSRC data)	Simple/complex tour generation for 8 trip purposes (sociodemographic characteristics, land use, local & regional accessibility) Mode choice (walk, bike, transit, auto) for 5 trip purposes (sociodemographics, land use, local & regional accessibility, Fully detailed walk and bicycle networks, physical attributes affect impedance
GIS-Accessibility Model	NCHRP 8-78 (Arlington, VA/MWCOG data)	Uses GIS layering to create accessibility scores for walk, bike, transit, and auto. Links mode choice with accessibility scores at trip origin and destination Estimates mode share at block level for HBW, HBO, NHB and WBO purposes Builds walk trip table (but does not assign) Highly visual presentation
Trip-Based Model Enhancements	NCHRP 8-78 (Seattle/PSRC data)	Strategic changes to traditional four-step TAZ model to improve sensitivity to land use and non-motorized travel Sensitizes auto ownership and trip generation to land use characteristics Performs pre-mode choice to distinguish inter- versus intrazonal trips Performs mode choice separately for intra zone (drive-alone, shared-ride, walk) and inter-zone (drive, shared-ride, transit, walk, bike) travel
Pedestrian Demand Models	PedContext and MoPeD (Univ. of MD/ Maryland DOT) Portland Pedestrian Model (PSU)	Modified four-step approach focused on estimating walk trips Walk trip generation for several purposes at PAZ level Creates walk trip tables, assigns trips to walk network
Bicycle Route Choice Models	San Francisco County Transp. Authority; Portland State Univ.	Models built from GPS-recorded trip data to predict choice of route for bicycle riders Quantifies importance of route characteristics (type facility, gradient, directness, traffic exposure)
Facility-Demand Models	Santa Monica Bicycle and Pedestrian Models (Fehr & Peers) Seamless Travel Bicycle and Pedestrian Models (Alta Planning & UC Berkeley)	Separate bicycle and pedestrian direct demand models Predict PM peak hour bicycle demand based on employment density, proximity to bike facilities, land use mix, and intersections Predict PM peak hour walk demand based on employment density, proximity to shopping, PM bus frequency, and traffic speeds

Finally, the "Facility Demand Models" are designed mainly for local project planning rather than regional or state forecasting models. Although it may be possible to enhance some of these models along the lines of the methods and examples provided below, such models are outside the scope of this project. In addition to the information provided in Report 770, readers interested in various approaches to direct demand models can also refer to Griffin (2009), Wei et al. (2013) and Le, et al. (2018).

The remaining sections of this chapter provide detailed descriptions and examples of approaches that are recommended to improve modeling of walk and bike trip demand, primarily in the context of regional-level activity-based or trip-based travel demand models.

5(B) USE OF MORE DETAILED SPATIAL AND NETWORK DATA

As discussed in the gap analysis in the preceding chapter, a key requirement of enhanced methods to predict walk and bike trips is that they are able to use more detailed spatial data than that typically used in TAZ-based model systems. The need for greater spatial detail applies to various aspects of the models, including the zone system, the networks, and the land-use data.

Using Microzones

TAZs and TAZ-based networks are necessary in a regional forecasting model to model the entire range of travel in the region across all modes and trip distances. However, TAZs are typically of the size that a large percentage of walk and bike trips are intrazonal (origin and destination within the same TAZ), or between TAZs that are close to each other. As a result, the impedance measures for the short trips tend to be inaccurate. To address this issue, many model systems have been adapted to use a second level of geography, typically called microzones or MAZs.

Most activity-based models use individual households rather than aggregate TAZs household segments to structure the model implementation system. This means that the software is designed to loop across households and persons rather than loop across TAZs and origin-destination TAZ pairs. Because the model structure is not tied to the TAZ system, it is feasible to include a more detailed MAZ geography in the same model system without adding a great deal to the system complexity or the computational burden that determines model run times.

The Sacramento Council of Governments (SACOG) and the PSRC activity-based travel models were developed using parcels as the basic unit of space, since both of those agencies maintain detailed and up-to-date land parcel databases for their regions. (See Bradley, et. al, 2010 for a description of the SACOG model system.) With over 500,000 parcels in each region compared to less than 4,000 TAZs, the spatial resolution of the parcels is more than two orders of magnitude finer than that of the TAZs. We will refer to the parcel-based approach as microzones for the purposes of further discussion.

Most other MPOs using ABMs have decided to use MAZs that are not as small as parcels, but still much smaller than TAZs. A typical approach is to use census block geography. Since it is important that MAZs nest within TAZs, MAZs are often defined as the intersection of census block geography and TAZ geography, meaning that census blocks are split into multiple MAZs if they cross TAZ boundaries. Using this approach, the number of MAZs in a region can range

from 20,000 to 150,000, depending on the size of the region. So, the spatial resolution of the MAZs is at least one order of magnitude finer than for TAZs. One of the first MPOs to use this approach was the San Diego Association of Governments (SANDAG). Since then, many other regions with ABMs have used a similar approach for defining microzones, including the MPOs for Jacksonville (NFTPO), the San Francisco Bay Area (MTC), Philadelphia (DVRPC), Denver (DRCOG), Nashville, Chattanooga, Fresno, and Phoenix (MAG).

An advantage of using census block geography is that census data on the number of households and persons is available to apportion TAZ-level population data down to MAZs. The Longitudinal Employer-Household Dynamics (LEHD) data is also available at the census block level. While this data may not be as accurate as some state-level and local-level employment databases, it does provide a convenient source to apportion TAZ-level employment to the MAZs. In some cases, the local employment and population point data sources may be good enough that there is no need to rely on census data. For example, Portland Metro is designing their MAZ geography to correspond to their all-streets network, rather than relying on census block geography that is not based on road or street network design.

While MAZs based on parcels or Census blocks may all have the desirable property of disaggregating the population and employment in the base year, there may be issues for future-year forecasting if a great deal of future scenario greenfield development is designated to take place within a single MAZ. In such cases, it is advisable to split the MAZs in the areas with high future development. (This same issue applies for TAZs but is even more important for MAZs.)

All-Streets Networks

While most TAZ-based regional networks contain only freeways, arterials, and enough local streets and connectors to provide connectivity to all TAZs, this level of detail is usually not adequate to model short-distance walk and bike trips that travel most of the distance on local streets. Adding a second level of network detail that includes all local streets is a way to address this issue. Using the methods described below, the all-streets network can be processed and maintained as a completely separate network from the regional TAZ-based planning network, although there may be advantages to maintaining and editing the two networks in a coordinated way.

Data on all-streets networks is typically available from sources such as Census Tiger files and OpenStreetMaps. It is important that the all-streets network be connected to each microzone (MAZ). If the MAZ system and the street network are detailed enough, it is often not necessary to add artificial connector links into the network. Instead, one can simply designate a network node (intersection) that is closest to an MAZ centroid as the “loading” point for that MAZ. Because the all-streets network is to be used for short trips, mainly including walk and bike trips, all limited-access highway links should be deleted from the network. Any important walking paths that are used as shortcuts should be added to the network if they are not already present.

General Use in Activity-Based Models

In combination, using microzones or parcels along with a detailed all-streets network serve three key functions in an activity-based model:

- More accurate distance, time, or other utility-based impedance measures can be calculated for short-distance trips, which include virtually all walk trips and the majority of bike trips (and a substantial fraction of auto trips as well). These impedance measures affect various choices in the model system, with the main effects being on mode choice and destination choice.
- On-street distances can be used for buffering land-use variables to provide neighborhood-level accessibility and attractiveness measures that are particularly relevant for walk and bike trips. (This is described in more detail in Section 5(C)).
- Destination choice models predict choices at the MAZ level rather than the TAZ level, allowing the more detailed accessibility measures for short-distance trips to influence the choice of destination—not just the choices of mode or travel route.

In activity-based models, the way that MAZs and all-streets networks are used in the models is typically through the following series of steps:

<u>Generating input data for the model:</u>

- A distance threshold is defined, within which MAZ-to-MAZ travel impedance measures will be used. Outside this threshold, only TAZ-to-TAZ impedances measures are used. A typical threshold value is 3 miles, a distance that includes nearly all walk trips and most bike trips.
- For all MAZ-to-MAZ pairs within this distance threshold, the shortest path is determined using a convenient network software package. (Most network software packages have the capability to process a list of origin-destination pairs rather than a full matrix.) The Python Pandana (Pandas Network Analysis) library has also been used to write code for such processing. Note that the shortest path is typically based only on distance, but later sections in this chapter provide examples where a more comprehensive generalized distance or generalized time measure can be used which is a function of distance plus other link variables such as facility type, grade/change in elevation, etc.
- As a full MAZ-to-MAZ matrix would be too large to be practical in most cases, the output of the process above is saved as a list of MAZ-to-MAZ origin-destination pairs within the distance threshold, along with the (generalized) distance for each pair. Note that bidirectional network symmetry can be assumed, which reduces the number of node pairs in the list by half. This assumption may be valid for walking if the only variable used is distance. If the network contains one-way links, or if information is used on grade or change in elevation, then bidirectional symmetry should not be assumed.

<u>Using the data in the model:</u>

- The MAZ-to-MAZ list is read and stored in memory at the beginning of the activity-based model run. As the list is read in, it is indexed by origin MAZ for fast access in memory. (The list is not a complete square matrix of the type used for TAZ-to-TAZ skim matrices, so indexing and binary search methods are used to quickly retrieve values from memory.)
- Whenever an impedance measure is required for an MAZ-to-MAZ pair for which the associated TAZ-to-TAZ skim distance is less than the “short distance threshold,” the MAZ-to-MAZ value is retrieved from the list stored in memory.

- To prevent a "cliff effect" from occurring at the short-distance threshold, it is possible to use a weighted average of the MAZ-to-MAZ and TAZ-to-TAZ impedance values, "blending" them on a sliding scale. This approach relies fully on the TAZ-TAZ measure at the distance threshold but relies more on the MAZ-MAZ measure as the distance becomes shorter, assuming that the network detail added by using the all-streets network is more important for the shorter trips. For intra-TAZ trips, the TAZ-TAZ value is fairly meaningless, so the MAZ-MAZ impedance value is used.
- This type of "blending" is most important for short auto trips, where the TAZ-TAZ skims include the effects of traffic congestion on speeds, while the MAZ-MAZ skims do not. For walk and bike trips, on the other hand, it may be best to use the MAZ-based measures out to the maximum radius for which they are available, as is done in several ABM implementations.

As described in examples later in this chapter, it is also possible to use a second level of increased spatial and network detail (microzones and all-streets networks) in combination with aggregate trip-based models. In those cases, the added detail is used in preprocessor or postprocessor modules that run before or after the main 4-step model components.

5(C) INCORPORATING LAND-USE EFFECTS IN MODE CHOICE

Several land-use variables have been found to be correlated with walk and bike mode shares. The variables often used in practical forecasting models include:

- Residential density – particularly near the home end of trips.
- Employment density – particularly near the nonhome end of trips.
- Number or density of public parks and public recreation areas.
- Mixed-use measures, described in more detail below.
- Intersection density, described in more detail below.
- Density of transit stops.
- Density of parking spaces of various types.

Since these are density measures, it is appropriate to calculate them within a consistent radius of each location, corresponding to typical walking or bicycling distances. The calculations are done using buffering methods, described below. First, we provide more detail on mixed-use and intersection density variables, which tend to be two of the most important land-use variables in the models used in practice.

Mixed-use measures

Neighborhoods with a mix of different land uses tend to attract more walk and bicycle trips. One reason is that there are a variety of different activities that people can participate in within walking and bicycling distance. Another reason may be related to self-selection—people who tend to make walk and bike trips are more likely to move to mixed-use neighborhoods. Self-selection in residential choice may mean that changes in land use will not lead to substantial changes in walk or bike trips in the short-term. In the longer term, however, assuming that the demand for housing in mixed-use neighborhoods will persist, the people who move into a neighborhood with an increasing mix of land uses will tend to make more walk and bike trips

than the former residents that they replace. With these assumptions, residential self-selection does not seem to be a major issue for longer-term forecasting models such as those used for regional long-range transportation plans.

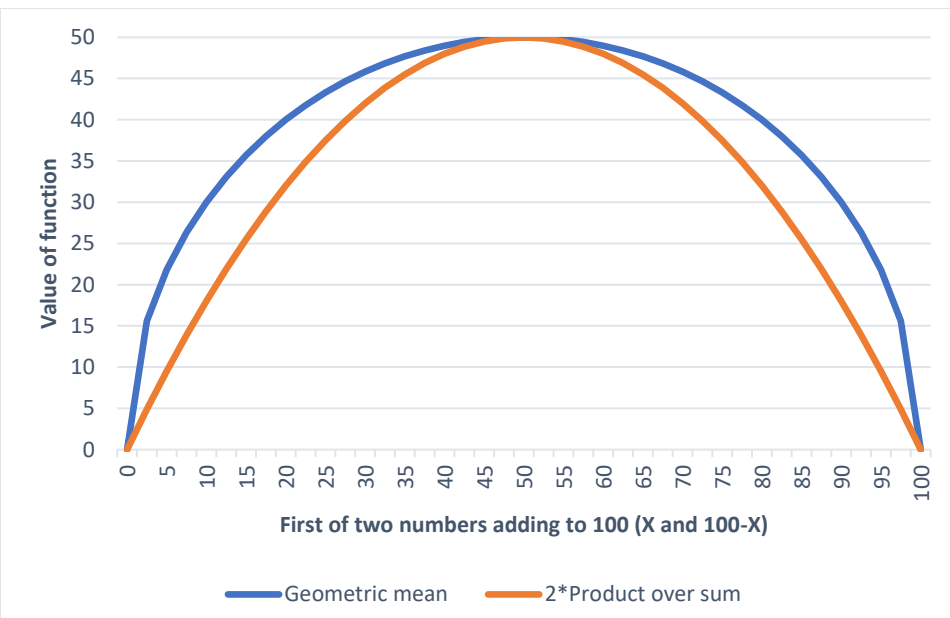
To measure mixed use, some models used in practice use a simple geometric mean of two different land-use values such as households and jobs (employment) within a TAZ or (preferably) within a buffer around a TAZ or MAZ. A geometric mean is the product of N numbers to the power 1/N. For two numbers X and Y, it is the square root of X*Y, while for three numbers X, Y and Z, it is the cube root of (X*Y*Z).

A similar measure is to use the product of two or more numbers divided by their sum. For two variables, households and employment, the equation is:

2* (Households x Employment) / (Households + Employment)

Figure 5.1 shows that both of these functions have similar shapes for the example of two numbers that add to 100. They both take value zero when one of the numbers is zero, and a maximum value when the two numbers are equal. Both functions also are linearly scalable, meaning that when the input values are multiplied by a factor of F, the output value is also multiplied by F.

Figure 5-1: Shapes of two common mixed-use functions with two land uses



A somewhat more complex type of mixed-use measure used in practice is an entropy measure. Frank, et. al (2006) use the following entropy-based measure for six land uses:

Land-use mix entropy measure = −A⁄(ln(N));

where area =

- A=(b1/a)*ln(b1/a) + (b2/a)*ln(b2/a) + (b3/a)*ln(b3/a) + (b4/a)*ln(b4/a) + (b5/a)*ln(b5/a) + (b6/a)*ln(b6/a)

- a = total square feet of land for all six land uses present in buffer

b1-b6 measure areas of land use for:

- b1= single-family residential
- b2= multifamily residential
- b3= retail
- b4= office
- b5= education
- b6= entertainment
- N= number of six land uses with area > 0.

This type of measure can be used for two or more different land. Although this example uses land area for variables b1 to b6, just two numbers, such as resident households and jobs, could be used instead. A variation on this measure adds one to each of the b values, so that a missing land use contributes zero to the numerator, while still contributing to the denominator N.

The entropy-type measure is similar to the geometric mean and product over sum in that it goes toward zero as the land-use mix tends towards a dominance of one use, and it has a maximum value of 1.0 when the proportions of all land uses are equal. In contrast to those other measures, the entropy measure has the property that it always takes a value between 0 and 1, regardless of the scale of the values (b1 to b6 in this example). As a result, it is less likely to be correlated with those values if they are used as variables in the same model.

Brown, et al. (2009) provide a detailed discussion of mixed land-use measures used to model walkability and found that a measure using six categories of land use performed better than measures using only two or three categories.

Intersection Density

A simple measure of local street connectivity is to count up all of the network nodes (intersections) in an all-street network within a buffer area. However, not all intersections are likely to be equal in terms of their effect on making an area more walkable or bikeable. In practice, three types of intersections can be counted separately:

- Four-way or more intersections: Nodes joining four or more street links.
- Three-way intersections (T-junctions): Nodes joining three street links.
- Dead-ends or cul-de-sacs: Nodes connected to just one link.

A simple intersection density measure is to add the number of the 4-way or more intersections plus the number of 3-way intersections and then subtract the number of dead-ends/cul-de-sacs, which generally have a negative influence on-street connectivity. One could also give the 3-way intersections a lower weight than the 4-way intersections, although we have seen no empirical evidence for setting such a weight.

In an area with a grid street network, street intersection density will be related to the inverse of average block size, which is also used as a measure for walkability in some models. Intersection density is more general, however, as it can also be applied for areas that do not follow a grid

street network with blocks, such as residential developments that have many curved streets and cul-de-sacs.

Buffering Methods

The simplest method for buffering is to simply add up a specific variable (households, jobs, transit stops, intersections, etc.) across all MAZs that lie within a specific threshold distance of a given MAZ centroid, using the straight-line distance calculated from the X and Y coordinates of the MAZ centroids.

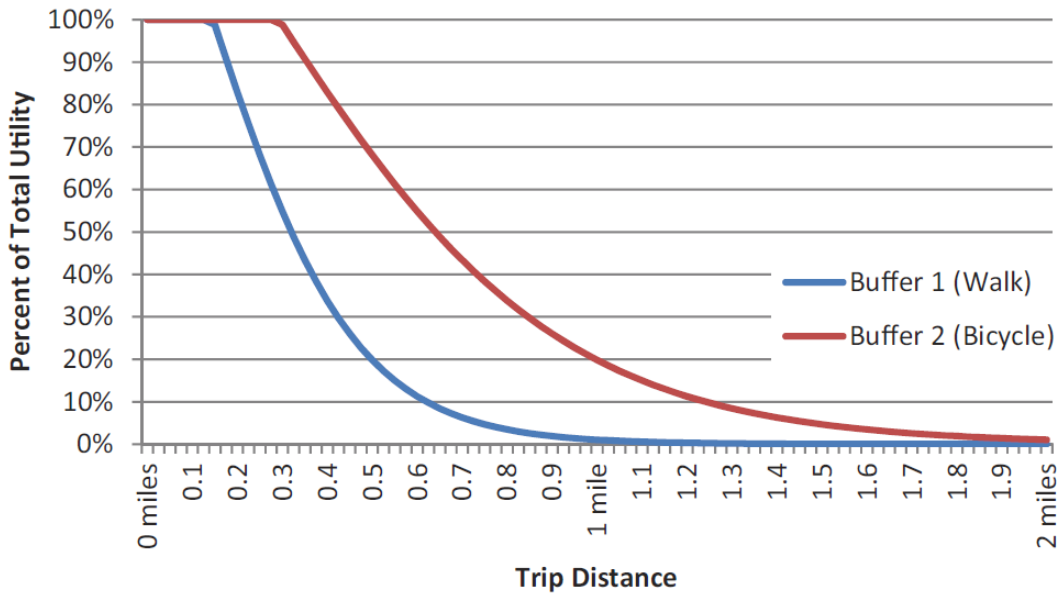
An improvement over the simplest method is to use street network shortest-path distance instead of straight-line distance. For activity-based models, the same list of MAZ-to-MAZ shortest-path distances that is used as input to the model, as described above, is also used as input to the buffering process. The key advantage of using on-street distance instead of straight-line distance is that it takes into account barriers in the street network caused by freeways, rivers, rail yards, airports, and other types of physical barriers that require circuitous walking or biking paths.

Another improvement is to use a distance-decay function to weight the land use within the buffer. Instead of giving the land use in each MAZ the same weight, a distance-decay function assumes that as MAZs are further away, their land use has less effect on the attractiveness for walking and biking. A distance-decay function also avoids “cliff effects” around an arbitrarily chosen boundary where, for example, an MAZ that is 1.01 miles away is not counted at all in the buffer, while another MAZ that is 0.99 miles away is counted completely. With distance decay, those two MAZs are counted with similar weights in the buffer, but those weights are much lower than the weight for an MAZ that is only 0.2 miles away.

Figure 5.2 shows the distance-decay functions that are typically used for buffering input data for the DaySim family of activity-based models used for several MPOs, including those in Sacramento, Seattle, Philadelphia, Jacksonville, Nashville, and Fresno. Land-use variables are accumulated within two buffers of different sizes—a smaller one that is more relevant for walking, and a larger one that may be more relevant for biking. The smaller buffer is flat until about 0.2 miles, and then uses a logistic decay function that drops to a weight of 0.5 (50%) at about 0.35 miles and drops to a weight of 0 by 1 mile. The distances for the second buffer are twice as large—flat to 0.4 miles, dropping to a weight of 0.5 at about 0.7 miles, and dropping to a weight of 0 by 2 miles.

Figure 5-2: - Examples of a logistic distance-decay functions used in buffering

Source: NCHRP Report 770 (Kuzmyak, et al. 2014). p. 37



In some other activity-based model systems, a negative exponential function is used for distance decay in buffering. This function has a similar shape to the logistic curves shown above.

While the buffering discussion above assumes that microzones (MAZs) are used, along with shortest-path distances on an all-streets network, it is also possible to use buffered land-use measures for a trip-based or activity-based model system that uses only TAZs, without an all-streets network. In that case, a distance-decay function could still be used, although a straight-line distance may be more accurate than using TAZ-to-TAZ shortest-path distances, unless the TAZs used in the model are quite small. TAZ size also affects the accuracy of the buffering process in general—the smaller the TAZs, the more accurate the buffer measures will tend to be.

Handling Correlations Between Land-Use Variables

An important issue in using land-use variables such as residential density, employment density, intersection density, and mixed-use measures is that they tend to be highly correlated with each other. This issue, referred to as multicollinearity, makes it difficult to estimate the separate effect of each variable in a model such as mode choice. If each of the variables is included in the model by itself without the others, it will show a positive estimated coefficient in the walk or bike mode utility function, but if all the variables are included at the same time, some will have positive coefficients and others negative coefficients, resulting from the high mutual correlations.

For the Philadelphia region (DVRPC) activity-based model, land-use variable functions were developed by first including each variable by itself to gauge the relative influence of each land-

use variable, and then including a single composite function of those variables in the mode choice models. The composite functions created are[5]:

For the bike utility:

1.0 * origin MAZ Buffer 1 mixed-use entropy measure
+ 0.00002 * origin MAZ Buffer 1 household density
+ 0.001 * origin MAZ Buffer 1 intersection density
+ 0.001 * destination MAZ Buffer 1 intersection density
+ 0.00002 * destination MAZ Buffer 1 total employment density
+ 1.0 * destination MAZ Buffer 1 mixed-use entropy measure

For the walk utility:

1.0 * origin MAZ Buffer 1 mixed-use entropy measure
+ 0.00001 * origin MAZ Buffer 1 household density
+ 0.001 * origin MAZ Buffer 1 intersection density
+ 0.001 * destination MAZ Buffer 1 intersection density
+ 0.00001 * destination MAZ Buffer 1 total employment density
+ 1.0 * destination MAZ Buffer 1 mixed-use entropy measure

The mixed-use entropy measure uses the entropy formulation from Frank et al. (2006) described above, but using four land-use variables – resident households, retail employment, service employment, and office employment. Note that although the larger Buffer 2 was also tested for the bike mode, using the measures from the smaller Buffer 1 for both walk and bike gave a better model fit in this case.

The resulting coefficients and t-statistics for the composite land-use variables in the key tour mode choice models (estimated based on data from the recent DVRPC household travel survey) are listed below. All of the variables have the correct sign and a t-statistic that is higher than the t-statistics for any of the variables if they are all estimated separately. In general, it is recommended to use composite functions of land-use variables such as those above to deal with the issue of multicollinearity.

Mode Choice Model	Variable	Coefficient	T-statistic
Home-based Work tours	Walk mode composite land use	1.36	6.4
Home-based Work tours	Bike mode composite land use	0.91	5.7
Home-based School tours	Walk mode composite land use	3.11	4.6

[5] This work was reported to DVRPC in model documentation in January, 2019, but no published documentation is available at this time.

Home-based School tours	Bike mode composite land use	2.15	4.5
Home-based Other tours	Walk mode composite land use	1.92	7.6
Home-based Other tours	Bike mode composite land use	1.26	6.9

The number or land area in public parks and public recreation areas is another variable that is buffered for some regions that use activity-based models. It is sometimes used as an attraction variable for recreation tours and trips in destination choice models, but has not been tested extensively for use in the walk and bike mode utility functions in mode choice models. It could also be used as a component in multiuse mixed-use entropy measures. Adding additional variables on parks and open space may be a promising topic for future model development.

Applying Findings from Bicycle and Pedestrian Route Choice Models

As described in Chapter 2, models of bicycle and pedestrian route choice have been fruitful topics for research. As described in this section, this research has been applied in practice in various ways.

Examples of Full Route Choice Model Application

One MPO that has rigorously applied and validated a bicycle route choice model within an activity-based model system is SANDAG. Castiglione, et al. (2014) provide a description of the model implementation and testing. As there was not sufficient local San Diego data to estimate a new bicycle route choice model, model parameters were transferred from models previously estimated in Portland, OR (Broach, et al 2012), San Francisco (Hood, et al. 2011), and Monterey Bay (Hood, et al 2014). All of those models were estimated based on GPS data that cyclists provided via smartphone apps.

Table 5.2 lists the bicycling route choice utility coefficients used in the model, along with the source of each one. Distance on the network is broken down by facility type, for various class of bike paths and lanes. A coefficient was asserted for “cycle tracks,” which did not exist in any of the three cities where models were estimated. Along with facility type, the model considers elevation gain, distance wrong way on one-way streets, total turns, turns at traffic signalized, and various types of turns at unsignalized intersections. The “log of path size” variable controls for overlapping segments of different routes considered in the choice set. (Distance on ordinary streets was a common variable in all models, so all coefficients from the three models were scaled relative to that variable.)

Table 5-2: Bicycling Route Choice Utility Parameters Used in the SANDAG Model

Source: http://onlinepubs.trb.org/onlinepubs/conferences/2014/ITM/Presentations/Monday/DynamicModelsDynamicData/jCastiglione.pdf

Variable	Coef.	Source
Distance on ordinary streets (mi.)	–0.858	Monterey
Distance on class I bike paths	–0.248	Portland
Distance on class II bike lanes	–0.544	Monterey
Distance on class III bike routes	–0.773	Monterey
Distance on arterials without bike lanes	–1.908	Monterey
Distance on “cycle tracks”	–0.424	–
Distance on “bike boulevards”	–0.343	Portland
Distance wrong way	–4.303	San Francisco
Elevation gain, cumulative, ignoring declines (ft.)	–0.010	San Francisco
Turns, total	–0.083	Portland
Traffic signals, excl. rights & thru junctions	–0.040	Portland
Un–signalized lefts from principal arterial	–0.360	Portland
Un–signalized lefts from minor arterial	–0.150	Portland
Un–signalized xing of & left onto principal arterial	–0.480	Portland
Un–signalized xing of & left onto minor arterial	–0.100	Portland
Log of path size	1.000	Constrained

The list of variables shows that the all-streets network used for the model requires a great deal of information to be coded, including bicycle facility types, elevation change, one-way vs. two-way streets, street/road class, and location of traffic signals. Figure 5.3 shows a diagram of the network for downtown San Diego (although the network covers the entire SANDAG region). The diagram indicates the density of streets, the location of traffic signals, and the extent of elevation change, with the steepest links generally north and east of downtown.

Figure 5.4 provides a schematic diagram of how the more detailed land use and networks are integrated into the SANDAG activity-based model, which is based on the CT-RAMP ABM software platform integrated with the TransCAD network modeling package. To the left of the diagram, it is shown that TransCAD provides TAZ-to-TAZ time and cost matrices for the auto mode, and TAP-to-TAP time and cost matrices for the transit mode. (See section 5(F) below for a description of enhanced TAP-based modeling of walk and bike access to transit.)

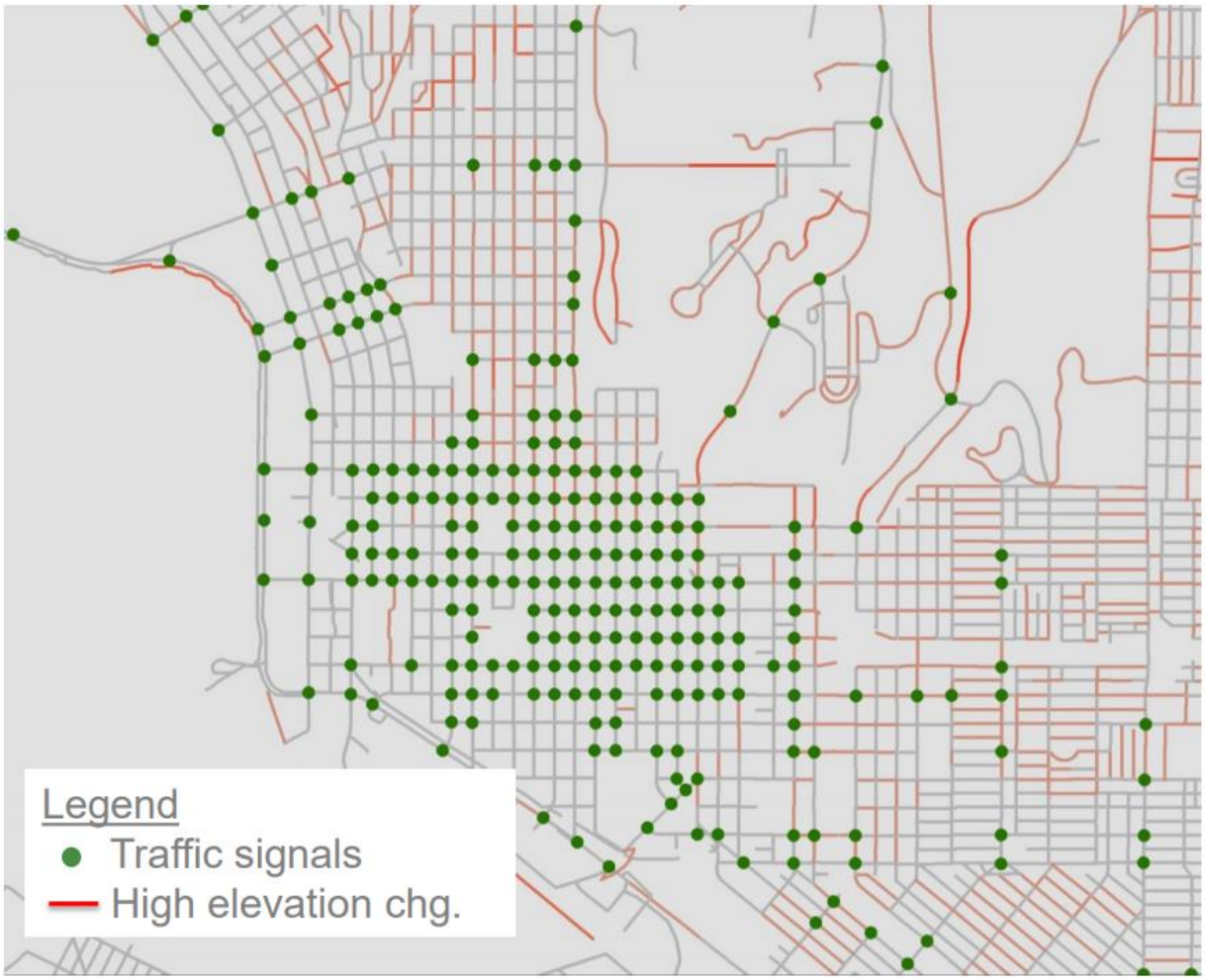
At the right of Figure 5.4, we see how the information for the walk and bike modes are used in the model. A custom Java program is used to find the best microzone-to-microzone (MGRA[6]-MGRA) and microzone to transit stop (MGRA-TAP) walk paths, using a function of both distance and elevation gain. These paths are generated up to a maximum distance of 2 miles. The

[6] SANDAG refers to microzones as Master Geographic Reference Areas, or MGRAs

output is listed as "walk cost," although this can be thought of as a generalized time measure, where a minute of walking up a steep hill is worse than a minute of walking on flat terrain.

Figure 5-3: Diagram of the active transport network for downtown San Diego

Source: http://onlinepubs.trb.org/onlinepubs/conferences/2014/ITM/Presentations/Monday/DynamicModelsDynamicData/jCastiglione.pdf

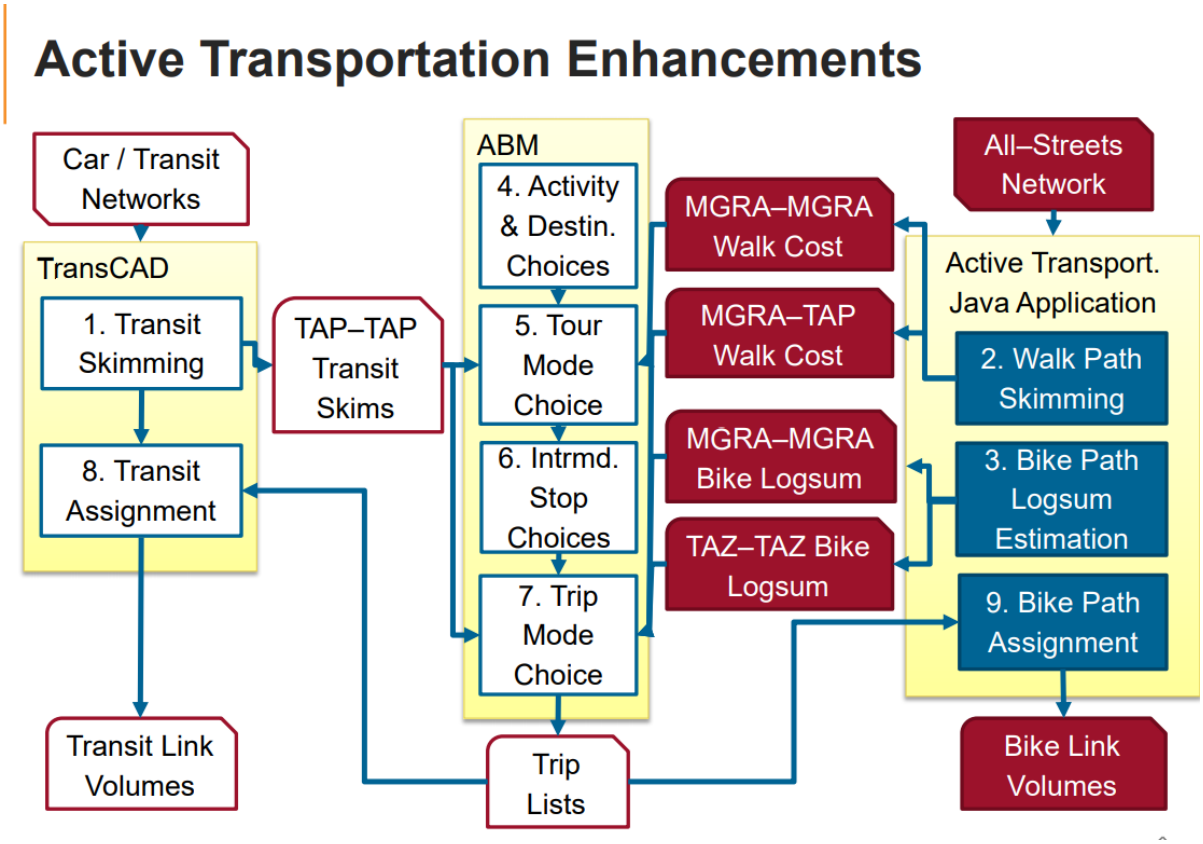


Box 3 in Figure 5.4 is where the bicycle route choice model is applied. Rather than supplying the "cost" or generalized time for a single best path, a "logsum" across a larger set of possible paths is calculated. In a logit probability model, the logsum is equal to the expected maximum utility across a set of alternatives, but it does not represent a single path. For distances up to 2 miles, the microzone-level (MGRA-MGRA) logsums are used in the bicycle utility for the ABM model components—particularly the mode choice models. For distances over 2 miles, the model is applied at the zone level to provide TAZ-TAZ logsums to the ABM choice models for all zone pairs up to 20 miles. The shift from microzones to zones at 2 miles is implemented to save run time, as the computation time would be long to apply the route choice model to all microzone pairs out to 20 miles. This approach does require, however, that all of the route choice variables that are coded in the all-streets network also be coded into the TAZ-TAZ planning network used

for car and truck traffic (with the exception that bicycles are prevented from using the freeway links in the TAZ-TAZ network).

Figure 5-4:: Schematic diagram of the enhanced SANDAG model system

Source: http://onlinepubs.trb.org/onlinepubs/conferences/2014/ITM/Presentations/Monday/DynamicModelsDynamicData/jCastiglione.pdf



The ABM produces a list of simulated, predicted trips. The bicycle trips in the list can be fed back to use the same bicycle route choice model for assignment to the network (Box 9 in the diagram), to obtain forecasts of bike volumes on specific network links.

The enhanced model was run and validated against available network counts. A program of bicycle counts had been done specifically for this project, because the amount of preexisting bicycle count data in the region would not have been adequate for model validation. One interesting finding is that the model was under-predicting use of bike trails near the coast north of San Diego, which are often used for recreational cycling. Methods were implemented to address this issue, including using distance from the coast as a variable in the destination choice model for recreation trips and in the bicycle mode choice utility for recreation trips.

The only activity-based model that we are currently aware of that uses a full application of a pedestrian route choice model is currently under development for the City of Copenhagen. Although this model is outside the US and no documentation is publicly available at this time

(expected in 2020), it is useful to describe some unique aspects of the Copenhagen model that may point the way forward for future applications in the US.

The weights relative to travel time that are used in the walk route choice model are shown in Table 5.3. The model is applied to produce route choice logsums for all zone pairs to a maximum distance of 5 km (3 miles). Although the Copenhagen model uses microzones, the TAZs are already quite small, with 4,100 TAZs in the region compared to 9,700 MAZs, so applying the route choice models at a TAZ-TAZ is reasonable.

Table 5-3: Coefficients used in Copenhagen walk route choice model, relative to travel time

(Source: Draft project memo: Walk Route Choice Model, October, 2018)

Attribute type	Parameter	Unit	Work	Leisure
Time	Travel time	[Minutes]	1	1
Elevation	0 = No hills	[Minutes]	0	0
	1 = Hills	[Minutes]	5.00	5.00
Type	0 = Separate path from road	[Minutes]	0	0
	1 = Path along road	[Minutes]	0.10	0.10
Land use	1 = Park	[Minutes]	0	0
	2 = Nature/scenic	[Minutes]	0	0
	3 = Low residential	[Minutes]	0.12	0.72
	4 = High residential	[Minutes]	0.25	0.85
	5 = Industry	[Minutes]	0.34	1.14
	6 = Mixed area	[Minutes]	0.30	0.90

The Copenhagen model also uses route choice models to produce TAZ-TAZ route choice logsums that feed into the bicycle and auto mode utilities. The bicycle route choice model uses a similar list of parameters as the walk route choice model in Table 5.3, but also uses variables for bike facility type, road type, traffic level, and surface quality.

The bike route choice model for Copenhagen is also capacity-constrained. Unlike any US cities at the current time, there is considerable bicycle congestion on some bike facilities in Copenhagen in some periods of the day—enough to discourage some cyclists from using those facilities. This means that the bike route choice model is run iteratively with bike trip assignment, as is done for the auto and truck traffic in most US travel demand models.

Examples of Simplified Applications

Full application of a bicycle route choice to produce logsum measures across a set of alternative routes is fairly complex and computationally intensive. A simpler way to use the coefficients of a bicycle or pedestrian route choice model, such as those shown in Tables 5.2 and 5.3, is to use them to identify a single best path through the network, and to measure the (dis)utility of that path in terms of equivalent miles distance or equivalent minutes of travel time. This method is similar to the way that the best transit path is often identified by transit path-building methods in network software packages. Although the logsum measure is superior in theory in capturing accessibility across a range of options, using a single shortest path is more practical in terms of

ease of implementation and computation time. and the greater practicality has attracted some agencies to adopt the simpler approach.

Examples of agencies that use this approach are the Sacramento (SACOG), Bay Area (MTC), Phoenix (MAG), and Fresno MPOs, as well as the San Francisco County Transportation Authority (SFCTA), which has its own activity-based model. Operationally, these simplified route choice applications work essentially the same way as for the SANDAG model shown in Figure 5.4, but they produce generalized time or distance measures for a single best path rather than producing a logsum across multiple paths. Either approach can be used for assigning the predicted trips to the network. The five agencies listed above all have a slight variation in the way that they apply the route choice functions:

- As shown in Figure 5.4, SANDAG uses a full bicycle route choice model for the bike mode but uses the best path from a simple walk route choice with two variables: distance and gain in elevation. The MAZ-level and all-streets network is used for walk trips and bike trips under two miles, while the TAZ-level planning network is used for longer bike trips between 2 and 20 miles.
- Like SANDAG, SFCTA uses the logsum from a transferred bicyclist route choice model for the bike mode, and the best path from a transferred pedestrian route choice model for the walk mode. This is done at the TAZ level. As a county agency, SFCTA uses detailed TAZ geography within San Francisco County, while using the MTC model TAZ system for the surrounding eight counties within the MPO region. The model also uses MAZ geography to get more accurate impedance measures for short-distance and intrazonal trips.
- SACOG uses a generalized distance for the best path for the bike mode with a simple impedance function focusing on distance by facility type. This is done at the TAZ level. For walk, a simple shortest-distance path is used. Like the SFCTA model, the SACOG model also uses MAZ geography to get more accurate impedance measures for short-distance and intrazonal trips.
- Like SACOG, the Fresno COG model uses a generalized distance for the best path for the bike mode, and a simple shortest-distance path for the walk mode. A unique aspect of the Fresno COG model, however, is that it uses MAZ-to-MAZ bike generalized distance skims for the entire region (Dhakar, et al 2019). This is feasible for the Fresno region because it has about 20,000 MAZs, so an MAZ-MAZ matrix is not too large to store in memory, as it would be for a region with 200,000 MAZs. The Fresno model is the only model we are aware of that is using an MAZ-level bike impedance matrix for the entire region. This feature makes it possible for Fresno COG to also assign all of the predicted bike trips at the MAZ-MAZ level to an all-streets network.
- MAG uses a bike generalized time utility equation based on various bicycle route choice models. The equation is used to skim the best bike path utility for each TAZ-TAZ pair, to use in mode choice and assignment. Unlike the examples above, this implementation was done for use with a trip-based model (RSG 2018).

Use with Trip-Based Models—A Preprocessor Approach

Over the years, several travel demand models have been developed that have a prestep to split trips into motorized and nonmotorized trips, before focusing on the motorized trips for the remaining steps of the modeling process. In those models, the presplit is typically done as function of local land-use and area type, since detailed network data on local bicycle and pedestrian infrastructure is not available.

An approach in the opposite direction is to use a premode-split approach to include more detail on local bicycle or pedestrian infrastructure. One such example is a pedestrian-based model design to be integrated with the Portland Metro trip-based model (Clifton, et al, 2016). Similar to the MAZs described in previous sections, the approach uses PAZs. In this case, the PAZs are grid-based, with each one approximately 80 meters x 80 meters, reflecting a one-minute walking distance. The Portland region includes about 1.5 million such cells, even more than the number of land parcels.

As seen in Figure 5.5, trip generation and mode split are modeled at this PAZ level, allowing detailed consideration of socio-demographic variables at a lever finer than TAZs, and also allowing use of fine-grained buffer measures of the local built environment. The built environment measures include sidewalk coverage, comfort facilities (benches, etc.), street traffic levels, and land-use mix variables. The destinations for walk trips are then predicted using a destination choice model, with random samples of "super-PAZs" (about 400 x 400 meters, somewhat larger than city blocks). The destination choice considers barriers to walking, such as freeways, rivers, and industrial areas, as well as attractions such as presence of parks.

Figure 5-5: A preprocessing approach to model pedestrian trips in detail

(Source: Clifton, et al 2016)

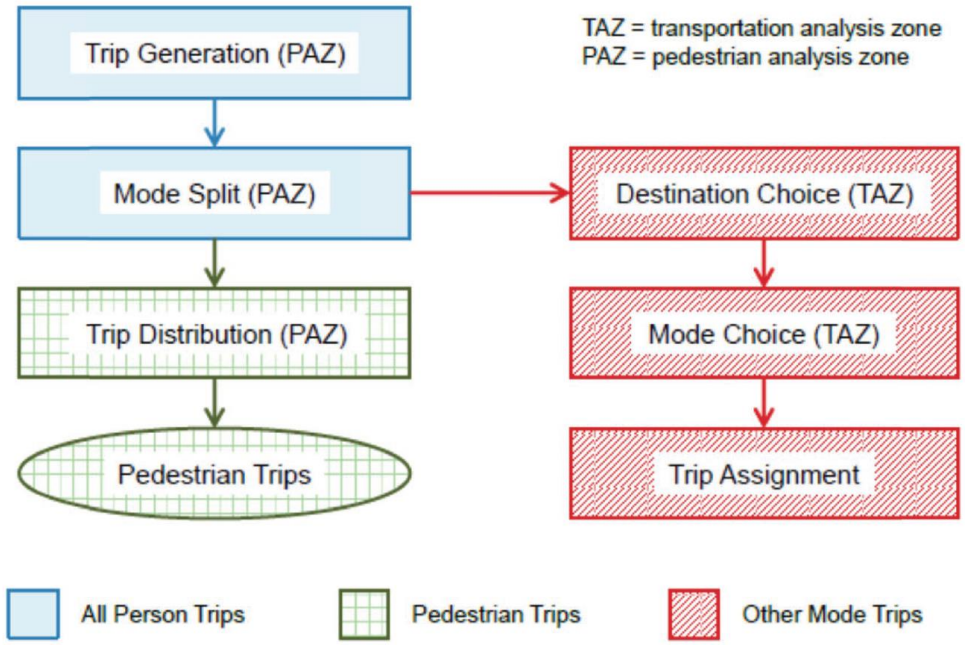


Figure 5.5 shows that the nonpedestrian trips are then used for the remaining three steps of the four-step model—trip distribution (destination choice), mode choice, and network assignment. One could also imagine a second preprocessing module where bicycle trips are split off using a level of geographic detail that is somewhere between the PAZ and TAZ geography. However, one possible criticism of this approach is the mode-split model at the PAZ level does not consider the relative attractiveness of the competing modes on the street network. That aspect may be acceptable for walk trips, which are mostly less than a mile in distance. However, it would be less acceptable for the bike mode, which competes with other modes over a range of distances.

Another comparable preprocessor modeling approach for walk trips is the PedContext model, developed and applied in Maryland. NCHRP Report 770 (Kuzmyak, et al 2014) provides a detailed discussion of the approach.

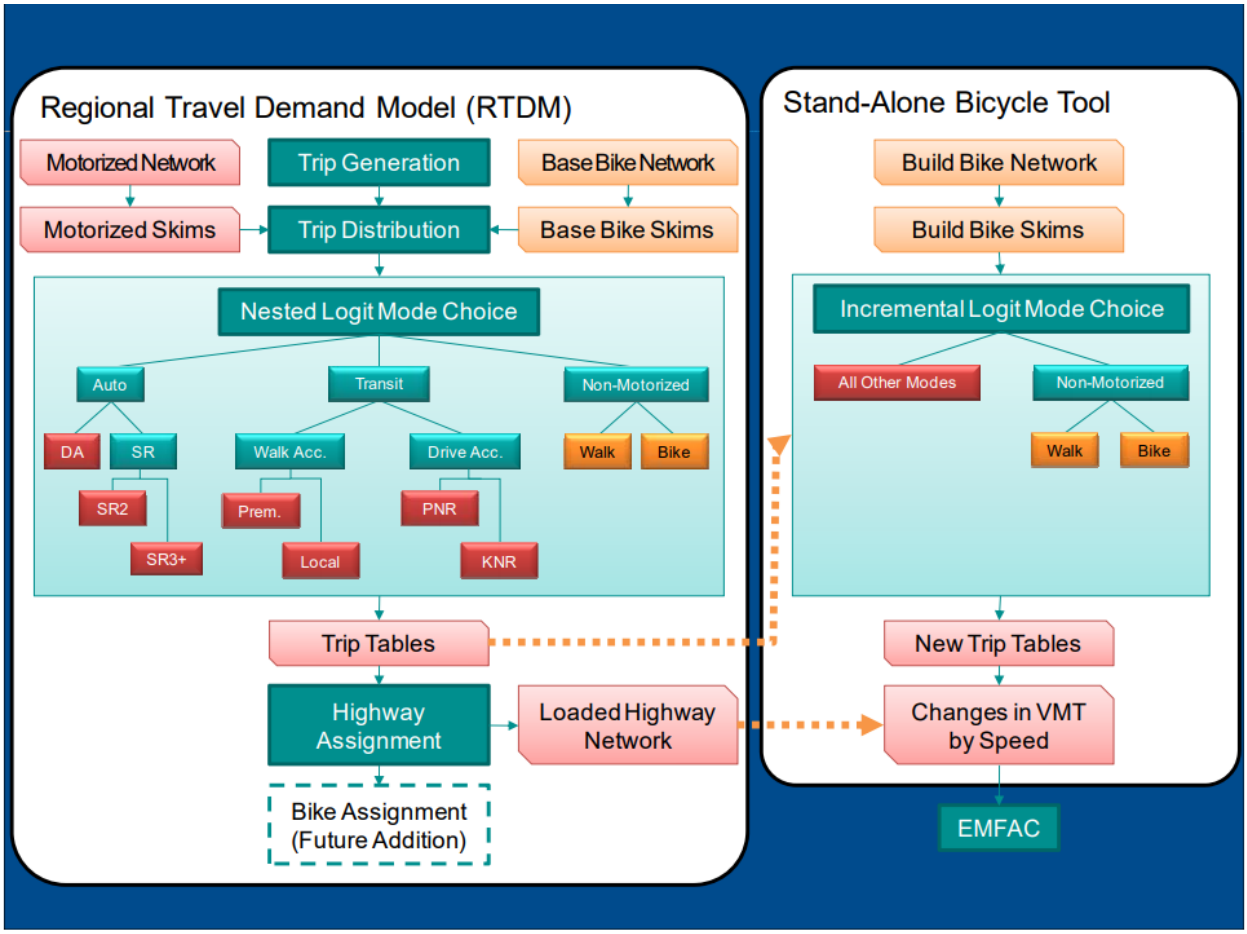
Use with Trip-based Models—A Postprocessor Approach

It is also possible to use the output from a trip-based model and then analyze or adjust the predicted trips based on future scenarios for bicycle or pedestrian infrastructure improvements. Hood, et al (2014) describe software tool created for the Association of Monterey Bay Area Governments (AMBAG) to improve their capability to estimate the emissions reduction benefits resulting from new bicycle facilities.

A schematic diagram of the model system is provided in Figure 5.6. The model system applies a bicycle route choice model estimated using GPS trace data collected from cyclists in the region via smartphone app. The route choice model produces a bicycle route choice logsum to represent the utility of the bicycle mode for each zone pair in the region, referred to as “bike skims” in the diagram. The trip-based regional travel demand model (RDTM) uses the bike skims for a base scenario to produce O-D trip tables for all modes. The auto trips are assigned to the highway network to generate estimates of highway link-level volumes and speeds..

Figure 5-6: The AMBAG Bike Model: A postprocessing approach to model the effects of changes in bicycle infrastructure

Source: ttps://ambag.org/programs/Modeling/AmbagBikeModel_KickOff_Presentation.pdf)



The stand-along bicycle tool is implemented with a graphical user interface (GUI) which allows the user to edit the edit the bicycle network attributes (e.g. add new infrastructure) to create a new "build" scenario. The bike route choice model is run for the changed network to create new logsum accessibility measures ("build bike skims"). The bike accessibility measures for the new scenario are compared to the measure for the based scenario ("base bike skims"), and an elasticity-based incremental mode choice model is applied to predict new trip tables for all modes, pivoting off of the original trip tables from the base model run. (The mode choice elasticity models were estimated using data from the California Household Travel Survey.) Finally, the emissions reduction can be estimated based on the distance and average speed of the vehicle trips substituted by bicycle travel, using a preexisting software tool such as the EMission FACtors (EMFAC) model used by California MPOs. The stand-alone bicycle tool was built to be easy to use in combination with travel demand models in other regions, although we are not aware of any other regions in which it has been used to date.

Another postprocessing approach was described by one of our postsurvey interviewees from the Albany, NY Capitol District MPO. There, the predicted trip matrices output from the trip-based model across all modes are used to analyze the potential number of bicycle trips in particular corridors, based on the purpose and distance of the predicted trips. Such an analysis can give an estimate of the potential use of new bicycle facilities in specific corridors, under different assumptions of diversion of trips from other modes in those corridors. This type of analysis is more suited to look at the potential for new bike or walk trips than to predict the number of such trips. The GIS-based accessibility tools described in NCHRP Report 770 can also be used in this way—to look at the current number of trips made in corridors or areas where relative accessibility by bike or walk can be improved.

Use with Trip-based Models—A Statewide Modeling Approach

The first generation of statewide models were exclusively focused on motorized (often only highway) modes of transportation. While many statewide models still exclude walk and bike trips, more recently some statewide models have begun to include them, albeit in a simple way. Several states' models including Tennessee, Michigan, Illinois, and North Carolina have adopted a common framework for handling mode choice including walk and bike trips.

In the context of these statewide models, the inclusion of walk and bike trips is not to support detailed pedestrian and bicycle planning. Rather, their inclusion in mode choice serves the following purposes:

- To allow the statewide model to accurately reflect higher walk and bike mode shares and consequently lower automobile mode shares and trips in the appropriate (walkable, bikeable) areas of the state.
- To allow the statewide model to reflect shifts in mode share to walk and bike with forecast development or redevelopment of land as walkable.
- To allow the statewide model to support scenario planning including scenarios with more or less pedestrian and bicycle friendly development.

These models are all similar in having an advanced trip-based or hybrid tour-based framework, and they include a simple mode choice model for residents' short-distance, home-based trips prior to destination choice. Since by definition every tour has two home-based trips, these models are essentially simple tour mode choice models. Non-home-based trips are generated separately by mode in this model framework as a function of the home-based trip (tour) mode. None of these models address the possibility of long-distance walk and bike trips given their extremely rare occurrence, and while visitor walk and bike trips are significant in some areas, none of these models have yet addressed these trips. In all of these models walk and bike have been represented in a composite nonmotorized mode, although there is no reason they could not be represented separately in this framework. Given the purpose of their inclusion and treated together in this way, the focus has generally been dominated by walk trips.

The mode choice model's specification is simple and is driven by traveler characteristics and simple mode level-of-service (LOS) variables. The utility function for the walk/bike mode is simply an alternative specific constant, a term for vehicle availability, and a walk/bike LOS term (with different parameter values for work and nonwork tours). The walk/bike LOS variable is derived through a multistep process in the base year, but results in a simple index value, on the scale from 0 to 1. For forecasting and scenario development, the LOS variable can therefore be assigned by reference to comparable areas in a straightforward way. This is important in practice as developing future-year or scenario-specific all-street networks at the scale of large states is generally prohibitive.

The walk/bike LOS variable is based largely on employment and intersection approach density. A composite density, which considers nearby retail employment, food employment, and households, is meant to capture whether stores and amenities are generally in walking distance. The variable also reflects decreased likelihood of walking and biking in areas with agricultural, mining, and especially industrial employment. Finally, a higher walk LOS variable is calculated for zones with greater intersection density based on an all-streets network. Zones with more intersection approaches per unit area have denser and more connected street networks that are more attractive for walking and biking.

While mixed land uses are important and activity diversity variables (such as Simpson's D statistic) have been helpful for similar modeling at an urban scale, given the large zones necessary for statewide modeling attempts to quantify mixture of uses is difficult. Large statewide model zones can include residences and retail but separated by distances that would require long walk trips. Therefore, rather than using diversity variables, the other factors described above are incorporated into the walk/bike LOS through multiplicative interaction rather than in additive form. Truncated Z-scores are therefore used to normalize the scales.

The walk/bike LOS variable for the Michigan statewide model is given below as an example:

$$Walk/Bike\ LOS = \frac{1}{1+e^{-0.8191 \times f_{Int} \times f_{Comp} + 0.7687 \times f_{Bas} + 1.921 \times f_{Int}}}$$

Where:

$f_{Int} = \ln(5 + \min(4, \max(-5, 1 + (Int - Int_{avg}) / Int_{std})))$

Int: intersection approach density (of the zone based on 0.5 mi buffer)

Int_{avg}: average of Int across all zones

Int_{std}: standard deviation of Int

$f_{Comp} = \ln(5 + \min(4, 1 + (Comp + Comp_{avg})/Comp_{std})$

Comp: composite density calculated as households + 4.1 x retail and food employment (of the zone based on 0.5 mi buffer)

$Comp_{avg}$: average of Comp across all zones

$Comp_{std}$: standard deviation of Comp

$f_{Bas} = \ln(5 + \min(4, \max(-5, 1 + (Bas - Bas_{avg}) / Bas_{std})))$

Bas: basic employment (agriculture, forestry & mining)

Bas_{avg}: average of Bas across all zones

Bas_{std}: standard deviation of Bas

$f_{Int} = \ln(5 + \min(4, \max(-5, 1 + (Ind - Ind_{avg}) / Ind_{std})))$

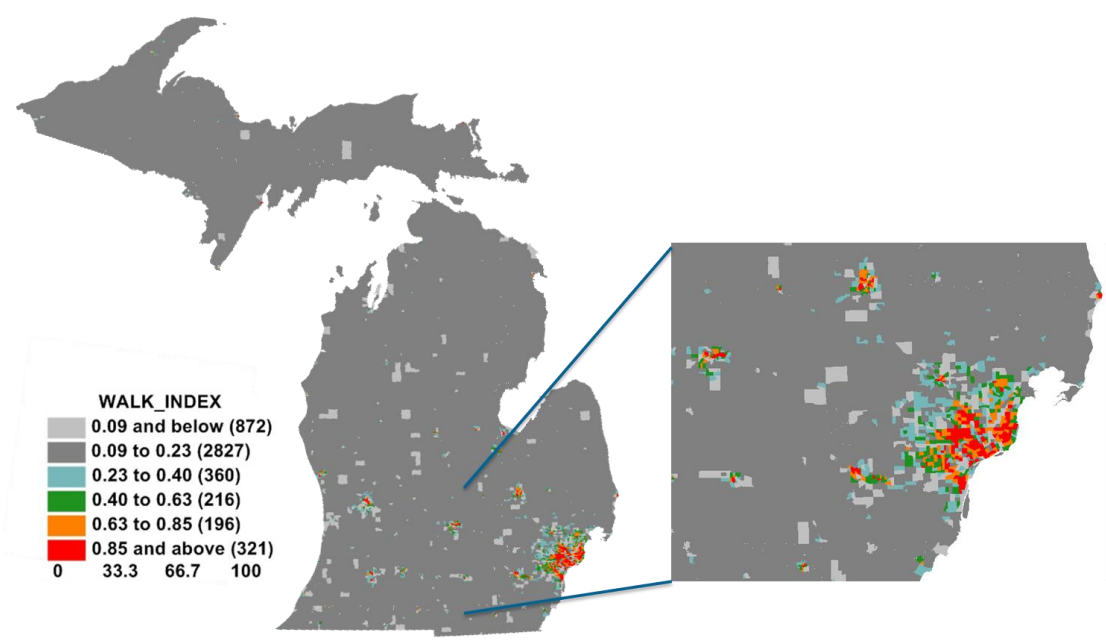
Ind: industrial employment

Ind_{avg}: average of Ind across all zones

Ind_{std}: standard deviation of Ind

Figure 5-7 below illustrates the resulting index variable for the Michigan statewide model. It is worth noting that the variable appropriately captures the quick transition from walkable to nonwalkable which occurs between areas, whereas, simpler variables based on additive functional forms often fail to capture this.

Figure 5-7. Walk/Bike Index in Michigan



5(D) ASSIGNING WALK AND BIKE TRIPS TO NETWORKS

Technically, it is possible to assign walk and bike trips to networks with any model that uses networks to generate walk and bike impedance measures to input to a mode choice model, regardless of whether that is done using a simple shortest-distance path or a complex route choice model. In practice, however, there are few agencies that regularly assign bike trips, and even fewer that regularly assign walk trips.

Examples of Bicycle Trip Assignment

Examples were provided in the preceding sections of several agencies that use assignment of bike trips, and some of the unique features of those examples:

- SANDAG was one of the first agencies to predict and assign bike trips using a fully detailed application of a bicyclist route choice model using transferred parameters (described above). The SANDAG model uses MAZ-level detail and an all-streets network for bike trips of up to 2 miles and uses TAZ-level detail and the regional planning network for bike trips of 2 to 20 miles. Because the computation time is fairly high using the fully detailed bicycle route choice model, SANDAG only assigns bike trips to the network for scenario alternatives where changes in bike volumes are of particular interest.
- The MAG trip-based model assigns bike trips based on a generalized time function applied at the TAZ level, and the assignment results were validated against observed counts (RSG, 2018).
- The Fresno COG predicts and assigns bicycle trips using a bike generalized distance function using transferred bicycle route choice parameters. The Fresno model uses MAZ-level detail and an all-streets network for all bike trips of all distances for the entire region. The consistency of being able to use the full level of spatial detail for all bike trips is an attractive feature which other smaller MPOs with fewer than 50,000 MAZs may wish to consider. (Another possible approach would be to use MAZ-MAZ detail only in a subarea of a region where cycling is more relevant and use TAZ-TAZ detail in the rest of the region. We are not aware of any agencies currently using that approach as a feature of their regional model, although it may be used in some cases in subarea versions of regional models.)
- The model being developed for the City of Copenhagen uses a detailed application of a bicyclist route choice model, using locally estimated parameters. The model uses TAZ-level detail, but the zone system and zone-based networks for the city are quite detailed, so moving to MAZ level is not a critical need. A unique feature of the Copenhagen bike assignment is that it is capacity-constrained, with feedback between the demand model and assignment. TAZ-TAZ bike route choice logsum matrices are generated for 10 different periods of the day (including one-hour periods in the AM and PM peaks) to represent varying levels of bicycle congestion during the day. The bicycle mode share in Copenhagen is roughly 40%, higher than in any US cities, so it may be some time before capacity-constrained bike network assignment becomes relevant in the US.

Examples of Walk Trip Assignment

Although agencies such as SANDAG and SFCTA use generalized distance measures to represent the impedance for walking, and Copenhagen is applying a fully detailed walk route choice model, we are not aware of any agencies that routinely assign walk trips to a network to analyze the output link volumes. It is interesting that 12% of MPO respondents in our on-line survey said that their agency assigns walk trips to a network (Table 3.10). Perhaps those respondents equate skimming the shortest network walk path with assignment of walk trips, or else perhaps there are local project analysis that use some type of pedestrian assignment and flow analysis.

5(E) MODELING WALK AND BIKE ACCESS TO TRANSIT

Most trip-based and activity-based models that include a transit mode consider walk access time to transit in one form or another. In some cases, the population in TAZs is split into segments according to the walk distance to the nearest transit stop, so that not everyone in a large TAZ is assigned the same walk access time to transit. Using MAZ geography in an activity-based model improves the accuracy, as the walk distance to the nearest transit stop can be calculated separately for each MAZ. In reality, however, transit users may use different transit stops or stations depending on which destination they want to reach.

Redefining the zone system for transit to use stations and stop areas

Several MPOs have activity-based models that use a separate zone system for transit than the TAZ zone system used for auto. These zones are commonly called transit access points (TAPs) and are located directly at transit station and stop locations. (In some cases, bus stops that are within a short walking distance of each other, such as 200 feet, are grouped into a single TAP). As is the case with MAZs, the household-based microsimulation structure of activity-based models makes it feasible to use separate zone systems for different modes without any major changes to the model system structure or run time.

The major advantage of using TAPs is that the transit time and cost matrices are station/stop-to-station/stop, and do not include any walk access or egress time (although they may include walk time to transfer between services). It is then up to the ABM software logic to find the best TAP-TAP pair to use to get from any origin MAZ to any destination

Modeling the Best Walk-Transit-Walk Paths

One of the first agencies to model transit using TAPs was SANDAG. The model schematic in Figure 5.4 shows that the walk path skimming method that produces MAZ-MAZ walk times also produces MAZ-TAP walk times for all transit access points within a certain radius of each MAZ. Then, when the ABM is looking for the best transit path between a given MAZ-MAZ origin-destination pair, it looks at all combinations of accessible TAPs at both the origin and destination ends to find the best MAZ > *walk* > TAP > *transit* > TAP > *walk* > MAZ path.

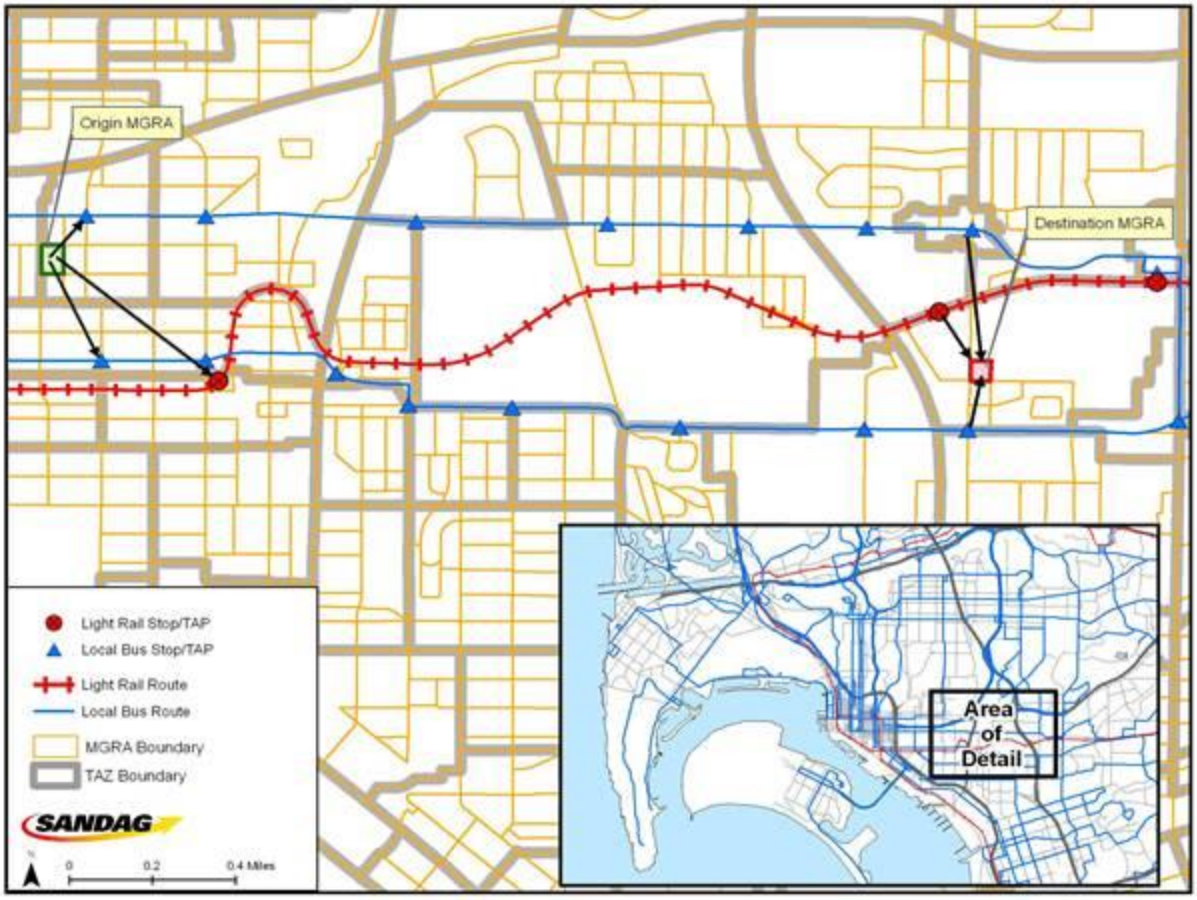
This approach to more accurately modeling walk access to transit is used in models in San Diego (SANDAG), the Bay Area (MTC), Chicago (CMAP), Miami (FDOT), Philadelphia (DVRPC), Southern Oregon (Oregon DOT) and Copenhagen. In several of these models, there are separate skim matrices for three different types of transit paths:

- Paths with local bus only.
- Paths with "premium" transit (rail or express/commuter bus) only.
- Paths with a transfer between local and premium service.

Including the different path types allows the model to assign different choices to people who have different trade-offs between factors such as walk access/egress time, transit fare, transit in-vehicle time, and the need to transfer.

Figure 5.8 shows how the approach is implemented for SANDAG (and similarly for the other regions listed above). The diagram shows one light rail route and two local bus routes, with TAPs located at stops along the routes. The diagram also shows walk access connectors from the origin and destination microzones (MGRAs) to the closest stops on each of the three routes. Using TAP-to-TAP matrices for the stop/station-to-stop/station transit travel times, frequencies/wait times and fares, and assuming relative (dis)utilities for light rail in-vehicle time, bus in-vehicle time, wait time, walk time, and fare, the MGRA-TAP-TAP-MGRA pair with the best utility is determined. Although not suggested by this figure, the access walk distances are typically measured as on-street distances using an all-streets network, rather than as straight-line distances.

Figure 5-8: A diagram of the TAP-based approach for representing walk access to transit



Rather than selecting the single best path, the SANDAG implementation calculates a logsum across up to four different paths with the highest utilities. Then, for assignment purposes, a single path is chosen from among the best paths using a random stochastic choice based on the relative utilities.

Extensions to Include Bike Access to Transit

The Phoenix region MPO (MAG) appears unique in including bicycle access to transit as a mode in a trip-based model in the USA (RSG, 2018). The bicycle utility on the TAZ transit access connectors is evaluated using the same transferred parameters from bicycle route choice models that are used to provide TAZ-TAZ utilities for the pure bicycle mode. Search for the best bike-transit-bike paths is done using the TransCAD transit path-building procedure, substituting the bike access impedances for the walk impedances that are typically used. In the model calibration, the model predicts 9,744 weekday bike-to-transit trips in the region, compared to 9,621 observed in the survey, a 1% difference. In total, there are about 175,000 daily transit trips in the region across all access modes, so bike access comprises about 5% of weekday transit trips, a similar percentage as both park-and-ride (6% of transit trips) and kiss-and-ride (4% of transit trips).

We are not aware of any activity-based models in the US that currently predict bike access to transit, although the TAP-based method for modeling walk access to transit described above can be extended to consider bicycle access as well.

The activity-based model for Copenhagen includes at least four different options for bike access/egress to transit, as additional transit modes in a nested mode choice model:

- Ride to the transit station, take the **bike on board** transit, and ride to the destination. (This is allowed only on trains. Buses in Copenhagen are not equipped to carry bicycles.)
- Ride to the transit station, **park the bike**, take transit, and then **walk** to the destination.
- Ride to the transit station, **park the bike**, take transit, and then **pick up another bike** at the destination station to ride to the destination. This could be a bike-share bike or one's own bike that is stored at the station. (Keeping a second bike parked at a rail station near work is fairly common in some European cities.)
- **Walk** to the transit station, take transit, and then **pick up a bike** at the destination station to ride to the destination.

Bike egress could also be used in combination with auto drive-to-transit access, although that is relative rare. The TAP-to-TAP method for modeling transit is well-suited to modeling so many different combinations of transit access and egress modes. Because the TAP-to-TAP skims only include the transit path, and not the access or egress portions, the same TAP-to-TAP skims can be used for all access/egress mode combinations.

5(F) TRAVEL SURVEY DATA FOR MODEL ESTIMATION AND CALIBRATION

In this section, we briefly consider the state-of-the practice in collecting and using travel survey data to estimate or calibrate travel demand models including walk and bike modes. First, it is useful to clarify the differences between model estimation and calibration. Model estimation involves estimating an entirely new set of parameters for a model, typically from local survey

data. Model calibration, on the other hand, means adjusting certain parameters in a model to match observed choices from local travel survey data. The parameters that are most typically adjusted in calibration are mode-specific-constants in mode choice models, or distance terms in destination choice models. The model that is being calibrated can be based on local data, one that is transferred from another region.

Model estimation typically requires complete data on all of the explanatory variables and choice variables in the models, and an adequately large sample size to provide statistically significant estimates for all coefficients and across important travel segments. Data used only for model calibration can be somewhat less complete if it is only used to calibrate certain models, such as mode choice. The sample size can also be somewhat smaller than that required for model estimation. For calibration, however, it is important that the survey data is weighted to be representative of the regional population along important household, person, and geographic distributions, because the weighted survey data is compared to model outputs for the entire regional population.

Stated Preference Data

Much of the early data on bicycle route choice was based on stated preference data (e.g. Bovy and Bradley, 1985, Wardman, et al. 2007). In recent years, less and less reliance has been placed on stated preference data, as more and more data from actual choices has become available.

Cyclist-Specific GPS Data

Most of the initial bicyclist route choice models were estimated using GPS trace data provided by cyclists using smartphone applications to record the route and speeds of their rides. The most common app of this type is the one created and managed by the Strava company. (Another is the CycleTracks app.) Figures 5.9 and 5.10 compare bike flows from the assignment from the Phoenix (MAG) regional model and regional data from the Strava app. While both have heavy bicycle flows around the university area in Tempe (lower center), the Strava data has a much higher concentration of trips in the area north of Tempe near Paradise Valley, while the model assignment has many more trips west of Tempe near the Phoenix City Center.

The discrepancy arises because using apps such as the Strava app is voluntary, and likely to attract cyclists who make long recreational trips—many on weekends, while the model predicts more utilitarian weekday bike trips.

Figure 5-9: Bike assignment flows from the Phoenix (MAG) model

(Source: RSG, 2018)

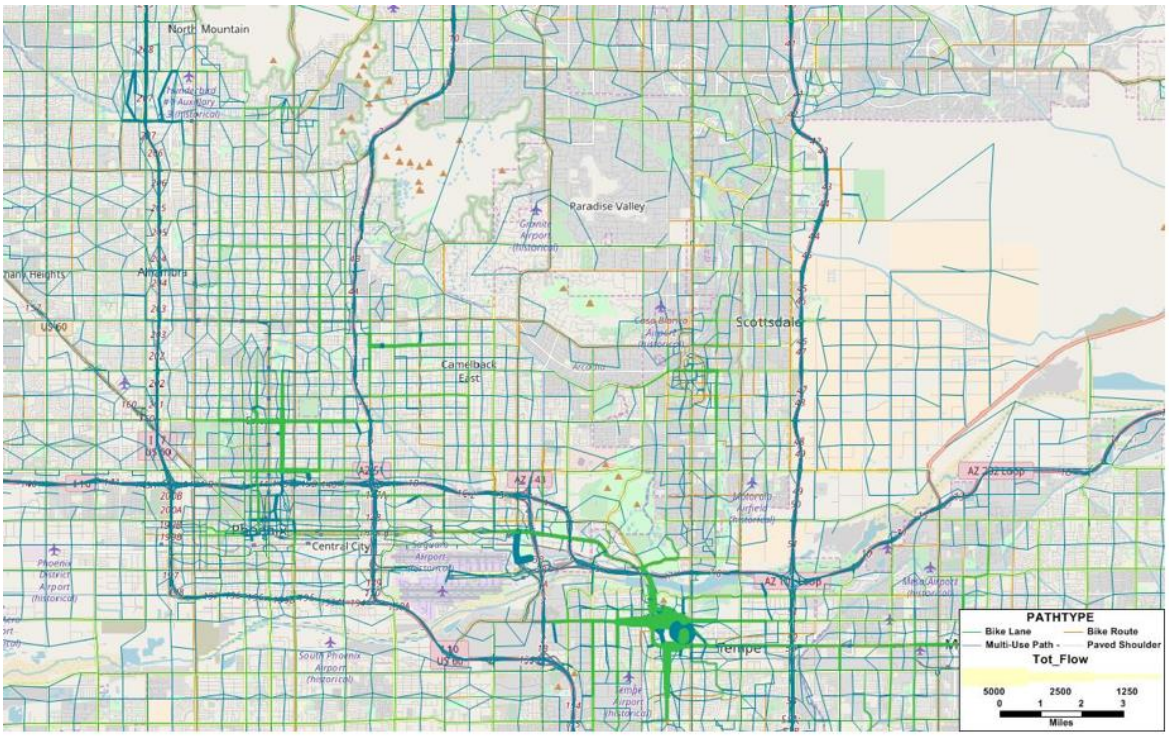
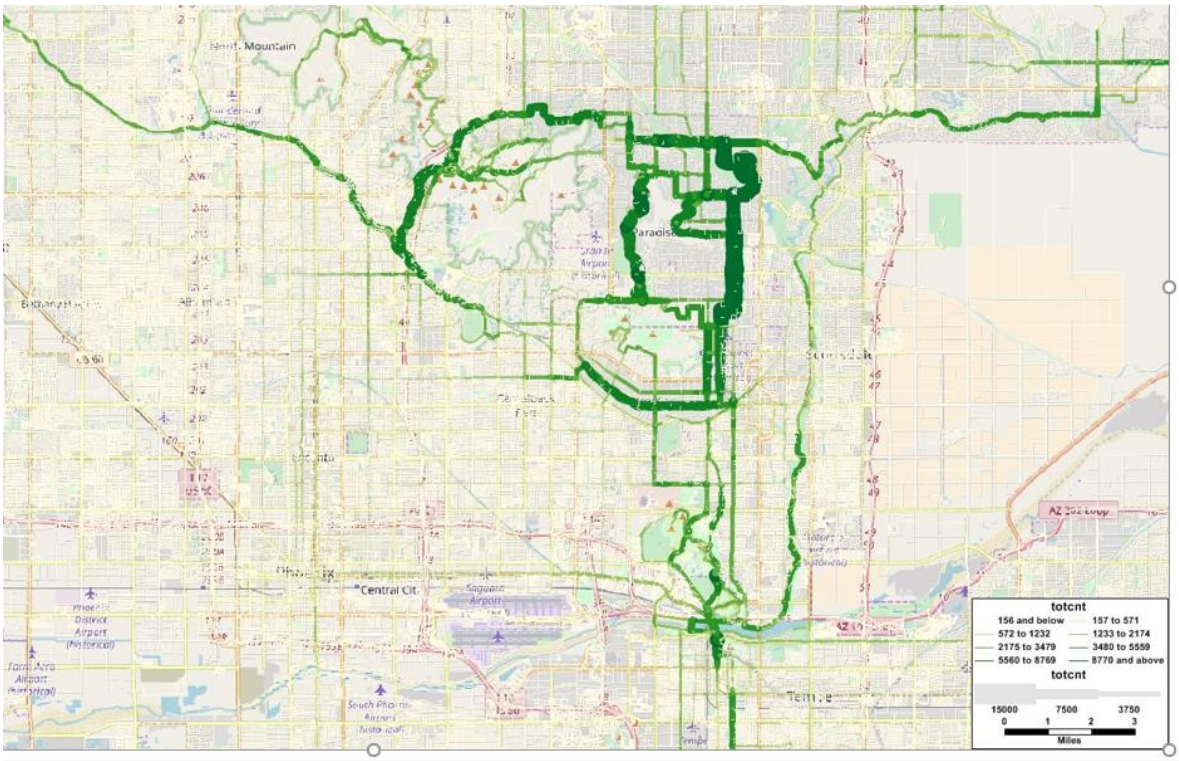


Figure 5-10: Bike flows from Strava data for the Phoenix (MAG) region

(Source: RSG, 2018)



Diary-Based Household Travel Survey Data

Traditional household travel surveys have been one-day surveys completed using travel diaries filled out by pen and paper, or reported via telephone. More recently, most travel diary surveys have been administered via the internet, using custom software. Because most travel diary surveys are carried out on weekdays, and tend to capture trips with fixed destinations better than they capture "loop trips" made for exercise, they have been better at capturing utilitarian walk and bike trips for work, school, errands, etc., than they have been at capturing recreational bike and walk trips made for exercise, dog-walking, etc. The biases are in the opposite direction of voluntary GPS apps such as Strava, but they may tend to go too far in the opposite direction and under-represent recreational trips and loop trips.

Smartphone-Based Household Travel Survey Data

In the last year or two, most new household travel surveys have been carried out via smartphone-based apps. Unlike the Strava-type surveys, the respondents are recruited via random address-based sampling, and the app captures all of their trips by all modes for a designated period, and not just the bicycle trips that the respondents wish to report. Although the data is passive in the sense that the smartphone is tracing all times and locations visited, the survey is active in asking respondents to state the purpose, (confirm the) mode, and other important details for each trip—all of the information that is captured in a diary-based survey. With the reduced respondent burden for smartphone-based surveys, most respondents are willing to provide details for up to seven consecutive days of travel. Capturing more days of data provides more observations for the nonauto modes such as walk, bike, and transit—modes which are used less than auto and for which there are relatively few observations. The smartphone-based surveys also exhibit less nonresponse bias than diary-based methods, capturing 15 to 20% more trips per day. They also capture loop trips such as walking around the block, which often tend to be omitted from diary-based surveys. Smartphone-based surveys also provide data on the routes used that can be used for route choice modeling. Overall, the trend toward smartphone-based surveys will improve the ability of household travel surveys to provide adequate data for modeling walk and bike travel.

Use of Geographic Oversampling for Household Travel Surveys

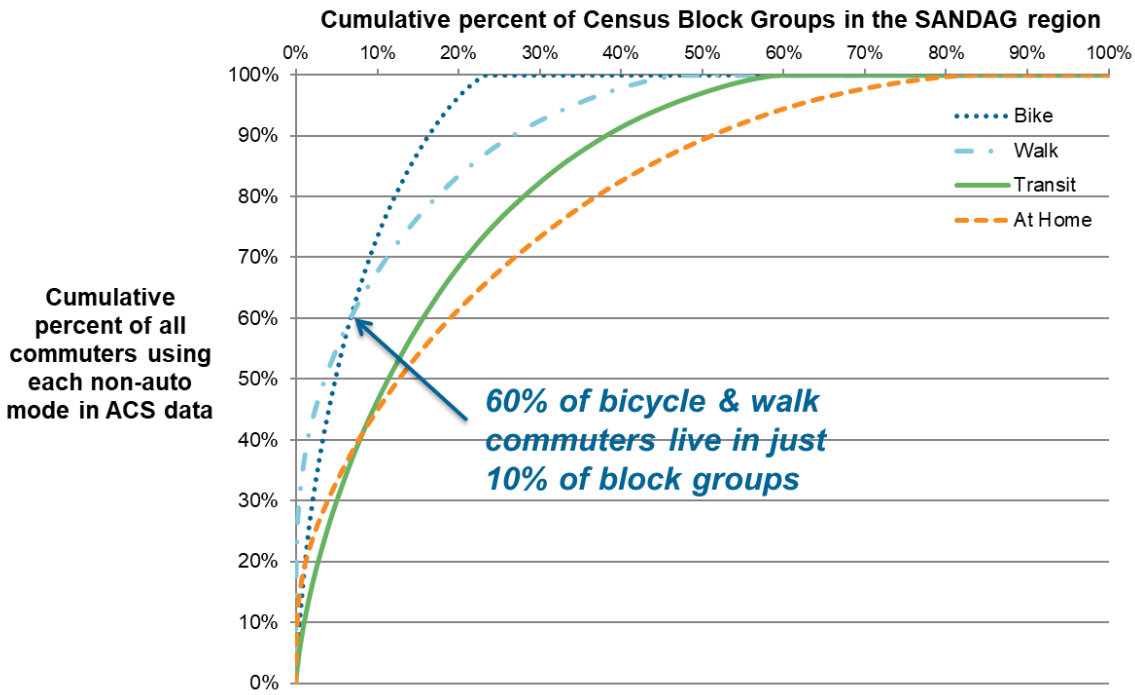
Because walk and bike mode shares are typically much lower than auto mode shares, the number of walk and bike trips obtained in household travel surveys is often not sufficient to support robust models to explain the choice of these modes. Figure 5.11 shows that according to ACS data for typical commute modes, 60% of those who usually commute by foot or by bike in San Diego County are concentrated in just 10% of the census block groups. Commuting by walk or bike is even more spatially concentrated than commuting by transit or working from home. Similar trends can be seen in ACS data from other regions.

By inviting a larger proportion of the residents of the block groups with the highest walk and bike shares to participate in a travel survey, it is possible to obtain many more observed walk and bike trips in the resulting data. (Although the ACS data is only for commute trips, neighborhoods with high walk and bike use for commuting also tend to have high walk and bike shares for other trip purposes as well.) Note that if geographic oversampling is used, the relative sampling

probabilities across block groups should be accounted for in the data expansion and weighting process.

Figure 5-11: Spatial Concentration of Walk and Bike Commute Trips in San Diego

Source: Bradley, et al. (2018)



5(G) TRAVEL DATA FOR MODEL VALIDATION

Bike and Walk Trip Count Data

Data for validating bike and pedestrian models is typically in the form of count data from specific locations and time periods. Validation against counts has been more common in practice for bike flows than for pedestrian flows, since few agencies assign walking trips to the network. In many regions, the collection of bicycle and pedestrian count data tends to be sparse and sporadic. For these reasons, projects to develop new or enhanced bicycle assignment models, such as the SANDAG and MAG projects mentioned above, have included budget to collect new bicycle count data to use for model validation specifically for that project. Likewise, any agency intending to develop new or improved capabilities to predict and assign bike trips should also consider collecting additional bicycle count data to use for validation. This means collecting data at more locations, as well as collecting data for more days at each location. Because bike trips tend to use a variety of major and local streets, a screenline approach collecting counts on a series of parallel alternative streets can be useful.

Collecting count data on some minor local streets may be useful even if those streets cannot be included in the modeled network. If the modeled network does not include all local streets, the modeled flows will tend to be higher than the actual flows on the included links because the model concentrates all flows on the included links, while in reality some cyclists use parallel

local streets that are not in the network. In that case, also collecting counts on some of the smaller local streets can help to reconcile differences between the predicted flows and counts on the modeled streets. (If possible, it is best to avoid this issue by including all streets in the modeled network, at least for the shorter distance trips that include most walk and bike trips.)

Origin-Destination Intercept Surveys

Origin-destination surveys provide more information than simple counts on links, as they provide information on O-D flows by travel purpose. Such surveys, however, require intercepting and stopping travelers to ask questions about origin, destination and purpose. A large sample would be required to make such data more informative than data from a household travel survey, and collection of such large intercept samples is becoming more and more difficult and expensive. Although stopping a cyclist or pedestrian to ask questions is logistically easier than stopping motor vehicles, such surveys are nevertheless quite expensive and are rarely used in practice anymore.

Passive "Big Data"

For modeling auto and truck travel, using so-called passive "big data" datasets has obviated the need for roadside origin-destination intercept surveys. Until recently, "passive data" mainly referred to data from cellphone data captured from cell tower signals. Now, however, location-based services (LBS) data, which includes a combination of GPS, Wi-Fi, and cell tower data, has replaced cell tower data as the main source of passively collected data. LBS data is collected on smartphones via hundreds of different apps that use the phone's location services, and this data is consolidated and sold by companies such as SafeGraph, Cuebiq, and others. Companies such as Streetlight and Sidewalk Labs have developed methods for processing such data into aggregate origin-destination matrices and providing web-based interfaces for querying the aggregate data. It is also possible for agencies or their consultants to purchase the disaggregate trace data and process it, although the sheer volume of the disaggregate trace data can make processing a formidable task.

Accurately identifying walk and bike trips in passively collected data is difficult for several reasons. Walk trips may be fairly easy to identify from the speed profile, a steady 2 to 4 miles per hour. However, passively collected data tends to be biased with respect to trip distance and duration—the shorter the trip, the less likely it is to be picked up in the apps and included in the data. As a literature review by Lee and Sener (2017) reports, however, the imputation of walk trips from LBS data is improving and walk trip O-D matrices from passively collected data show promise to be increasingly accurate and available over time.

Bike trips are more difficult to identify from passive trace data, particularly in congested urban areas, because their speed profiles are not that different from those of automobiles (and in some cases may even be faster than automobiles). Imputation may be easier in areas with steep changes in elevation, as bike speeds are much more sensitive to gradients than auto speeds are. The low percentage of trips that are bike trips in most regions makes imputation subject to a greater margin of error than imputation for more common modes.

Fusing passively collected data with other data sources may be the most promising approach for imputing bike trip matrices. Proulx and Pozdnukhov (2017) describe a method to estimate bicycle volume across the networks in San Francisco. Researchers fused Strava Metro data with bike-share program data, manual and automated count data, and data from two regional full-population travel demand models. The results revealed that combining the given data improved model predictive accuracy. In the future, fusing passively collected data with smartphone-based GPS household travel survey data may also help to better impute bicycle trips.

CHAPTER 6. RECOMMENDATIONS FOR ADVANCING THE STATE-OF-THE-PRACTICE FOR MODELING WALKING AND CYCLING

6(A) INTRODUCTION

Based on the discussion in the preceding chapters, this section provides summary recommendations on advancing the state-of-the-practice for modeling and walking and cycling, for various types of models and model users. The methods recommended vary according to the level of complexity, the level of effort, and the amount of local data required.

6(B) RECOMMENDATIONS FOR TRIP-BASED MODEL CONTEXTS

Although most of the examples provided in Chapter 5 are for activity-based models, it is possible to achieve many of the same types of improvements in more traditional aggregate trip-based models. Key areas for potential improvement are:

- Including walk and bike as separate nonmotorized modes in mode choice. The impedance measures for these modes can be based on simple network shortest-path distance measures, although we suggest enhanced measures below.
- Including car ownership variables in the utility for walk and bike (and transit), preferably using a car ownership model that is integrated into the model system. Segmenting households into three segments is recommended: (a) no cars in the household, (b) 1+ cars in the household, but fewer cars than adults, and (c) 1+ car per adult in the household. (Note: Cars per worker can also be used instead of cars per adult.)
- Adding geographical detail to the zone system by using smaller TAZs, particularly in denser areas with the highest potential for walk and bike trips.
- Adding detail to the network, moving in the direction of using an all-streets network. (This is most feasible for regional models that use finer spatial detail on the zone system, and the least feasible for statewide DOT models or MPO models for large urban regions.)
- Using smaller TAZs or more network detail to also model walk access to transit more accurately.
- Adding walk- and bike-specific attributes to the networks to the extent possible, such as existence of various classes of bicycle lanes and paths, measures of gradient or changes in elevation, and identification of barriers to walking and cycling, such as freeways and rivers.
- Using more land-use variables in the models, such as mixed-use measures, street connectivity measures such as intersection density, and presence of public parks. Using consistent buffering methods to measure these variables is also recommended.
- Alternatively, particularly for statewide models or other situations where more detailed networks and zonal detail are not practical, using index variables for walkability/bike suitability. Best practice is to estimate these attributes for the model base year using GIS data such as intersection approach density, presence of sidewalks and paths, mixed-use development, etc., and then using base year reference cases for developing future-year scenarios.

- Using generalized distance or time measures from route choice models instead of shortest distance alone to select the best walk and bike paths and set their utility in mode choice models. The enhancements to the Phoenix (MAG) trip-based model (RSG, 2018) are an example of how this was done for the bike mode, as well as for bike access to transit.

Preprocessing Tools

Preprocessing approaches exist such as that described by Clifton, et al. (2016). Such an approach is most suited for using fine-grained microzones to model walk trips before processing the nonwalk trips using the existing trip-based model. It is suited for walk trips more than for bike trips because it focuses on short trips in small areas, without explicitly modeling the attractiveness of competing modes on the street network.

Postprocessing Tools

The tool created for the Monterey Bay MPO (Hood et al, 2014) is a good example of a transferable approach, providing a user-friendly interface to specify future bicycle network scenarios, and then using a bicycle route choice model to evaluate the resulting change in the attractiveness of the bike mode for each TAZ pair, and applying elasticities to the trip tables output from the regional trip-based model to attract trips from (or lose trips to) the competing modes of auto, walk and transit. The software tool also evaluates changes in emissions resulting from the mode shifts across all zone pairs.

Other postprocessing methods, such as that used by the Capitol District MPO in Albany, NY, analyze the trip tables resulting from a trip-based model by distance and purpose to gauge the potential for walking or cycling in specific corridors or subareas, or to identify which corridors or subareas have the most potential. The GIS-based accessibility tools discussed in NCHRP Report 770 could also be used for this purpose, in combination with trip tables predicted from an existing travel model. As passive origin-destination data improves in quality and becomes more affordable, such methods could also be applied to origin-destination matrices from passively collected data instead of trip tables produced by models. Such approaches are useful as quick-response methods to assess market potential, in contexts where more elaborate forecasts are not required.

6(C) RECOMMENDATIONS FOR ACTIVITY-BASED MODEL CONTEXTS

Several examples for enhancing activity-based models were presented in Chapter 5. In many ways, the list of recommended improvements for ABMs is similar to the list provided for trip-based models above. However, the household-based microsimulation structure of activity-based models provides more flexibility in how the improvements can be implemented. Key recommended enhancements are:

- Activity-based models have the flexibility to add geographical detail to the model system by using a second layer of geography, typically called microzones (MAZs). A convenient way to create microzones is to use the intersection of census blocks and TAZs, although using parcels or some aggregation of parcels is also possible. As with trip-based models, using more and smaller TAZs can also be useful.

- Adding network detail to a regional model system by using an all-streets network, which can be processed at the MAZ level to provide accessibility measures for short-distance trips, which include most walk and bike trips. As with trip-based models, adding more local streets to the TAZ-based planning network is useful as well, particularly for modeling bicycle trips.
- Adding walk- and bike-specific attributes to the networks (both the all-streets and planning networks) to the extent possible. This includes existence of various classes of bicycle lanes and paths, measures of gradient or changes in elevation, and identification of barriers to walking and cycling, such as freeways and rivers.
- Using land-use variables such as mixed-use measures, street connectivity measures such as intersection density, presence of public parks, and residential and employment density, particularly in the mode choice utility equations for walk and bike. Using distance-decay buffering methods based on on-street distances to measure these variables is also recommended. Use of composite functions of these variables is recommended in model estimation to address the issue of high correlation between the variables.
- Using generalized distance or time measures from route choice models instead of shortest distance alone to select the best walk and bike paths and set their utility in mode choice models. Using logsum measures from a fully-applied multipath bicycle route choice model is another option, although this involves greater complexity in programming and longer computation time.
- The structural flexibility of activity-based models makes it feasible to use separate zone systems for the auto and transit modes, using a separate zone system of TAPs located at transit stations and stops (areas) to improve the modeling of walk (and bike) access to transit. TAP-to-TAP transit time and cost matrices only include the transit path itself, but not the access and egress portions of transit trips. MAZ-to-TAP walk distances are combined with the TAP-to-TAP skims to find the best walk-transit-walk path between any MAZ origin-destination pair. This method can be extended to various options for bike access to transit as well. This is a more major change to the model system than the others listed above, and is mainly recommended for regions with extensive, multimodal transit systems. In addition to improving the modeling of walk and bike access to transit, it has the benefit of more accurately modeling the transit network and transit use.

The model enhancements in the above list are already implemented in some transferable activity-based model software platforms. If these options do not already exist in the ABM software platform being used, it may require considerable work to add them If they do already exist in the platform being used, the extra work for the agency is primarily in specifying, building, and maintaining the additional input data that is required for these enhancements, both for the base year and for forecast year scenarios. For forecast years, it can be appropriate to leave the all-streets network used for short-distance calculations as is, since these calculations do not use freeway links and are not sensitive to the capacities on other arterials. The exception to this is a recommendation to add MAZs and network detail in greenfield areas that are sites for extensive development in future scenarios. (This can also apply to adding TAZs and planning network detail in such areas.)

Software Advances

Clearly, the recommendations given above are more likely to be adopted if they can be implemented relatively easily within preexisting, well-documented, user-oriented software packages. The major network modeling software packages in which most trip-based models are scripted and implemented (TransCAD, Cube, EMME, Visum) have interfaces for editing networks and zone systems. They also have internal GIS capabilities, or linkages to external GIS software, that facilitate buffering and other operations on land-use data. As agencies implement improvements in modeling walk and bike trips within these platforms, it would be valuable to build up a library of example scripts, GIS processes, and other auxiliary processes (with documentation) that other users can transfer to their own regions. This would be valuable for both trip-based and activity-based model users, as the activity-based software platforms are interfaced with these same network modeling packages.

As the number of users of activity-based models has grown, there has been more of an effort to make the software platforms consistent and configurable across different users, so that any agency can use model enhancements that have been implemented for other agencies. As an example, the DaySim software platform, which currently has 12 user agencies, has been configured to use a single consistent open-source codebase across all users, with a testing and integration system to ensure that any enhancements implemented for one user are also compatible with all other model implementations (Stabler, et al 2017). The code and documentation are available to all users (and nonusers) via GitHub.

Another example is the ActivitySim project to build the next-generation platform for activity-based models (Stabler and Doyle, 2017). This is a collaboratively-funded project across a growing number of partner agencies within AMPO (currently six agencies). Following the DaySim example above, the platform is a single code base that can be used and customized by many users, with each user able to transfer new features that have been added by/for other users. The emphasis for ActivitySim is to the make model interface much easier to use and adapt than any of the existing ABM software platforms.

As mentioned above, much of the effort in implementing model enhancements for walking and biking is in preparing the additional model input data that is required. To that end, much effort still needs to be put into better tools for compiling, editing and checking spatial and network data in the particular forms that are required for the model systems. The ideal is a “data pipeline” that will extend all the way from travel surveys and passively collected data and other validation data (count data, transit ridership data, speed data, etc.), through the forecasting model system, and also facilitate storage and visualization of model results at the other end. For analyzing walk and bike trips, any visualization tools need to work a high level of spatial resolution. A great deal of work for creating such data tools has been done, but there is still much more that needs to be done to ease the data preparation and maintenance load for model users.

Another category of tools is stand-alone tools that can be used with the outputs of a travel demand model, or tools that can be used with passively collected data or GIS data as a substitute for using a full travel demand model that includes walk and bike modes. NCHRP report 770

contains detailed descriptions of several tools along these lines. An example in this report is the postprocessing tool for bicycle network improvements described in Hood et al (2014).

6(D) RECOMMENDATIONS FOR FUTURE RESEARCH

Much of the work needed to advance the state-of-the-practice in the coming years will be to further refine and disseminate the types of methods described in this report. In addition, we provide some specific recommendations for future research:

Research into data standards and transferable data and data tools: Much of the effort required to implement most of the recommended advances in practice is involved in acquiring and maintaining more detailed spatial data, including networks, network attributes, (micro)zone systems, and land-use attributes. Advances have been made to provide more standardized and accessible data and tools, including OpenStreetMap and Google Point of Interest data. Further advances along these lines could make it much easier for agencies to implement new walk and bike modeling approaches. For example, the Zephyr Foundation has started a project on Network Data Standards and Management Tools (Zephyr, 2019).

Crossregional Studies: Transferability of Walk/Bike Behavior and Models

There have been several studies comparing estimated models and behavioral findings, some of which are in the literature review in Chapter 2. However, there has not yet been a study to compare models for predicting walk and bike trips as implemented in practice. The models (and methods) can be compared in terms of how well the models transfer from one region to other regions in terms of validation against observed behavior and in terms of their sensitivity to infrastructure and land-use changes.

Use of passive "big data": how to better impute and expand walk and bike trips

Any research into using passively collected data is affected by the rapid changes in the technology and availability of the data, as well as imminent changes in data privacy laws that will influence how the data can be used. In that context, it will be important to continue to investigate and enhance methods for imputing walk and bike modes in passively collected data to create useful origin-destination matrices of walk and bike trips. It is likely that data fusion methods—using passively collected data together with smartphone-based household travel survey data, count data, and potentially other types of data—will be needed to make optimal use of passively collected data.

Further research into the separate effects of aging and generational change (age cohorts) on the propensity of walking and biking: There is consistent evidence that people tend to walk and bike less (fewer trips and shorter trips) as they age, particularly above age 55. However, there is some evidence from longitudinal data that once true age effects have been taken into account, newer generations are walking and biking more than earlier generations (RSG, 2019). Continued research focused on age-cohort differences may be valuable, including recommendations on how such trends should be incorporated into longer-term forecasting models.

Methods to Better Incorporate Latent Attitudinal Variables

New modeling approaches such as ICLV models are emerging that can incorporate attitudinal variables within a discrete choice model framework that potentially can be applied in practice. A recent example is the study by Rossetti, et al (2018) using latent perceptions of safety for different types of cycling infrastructure in route choice. We recommend studying ways to integrate these types of models into practical settings—either as stand-alone tools or as part of regional models

A new competing mode: transferability of the methods to shared electric scooters

With the rapid (and often controversial) emergence of shared electric scooters, many agencies are looking for ways to include this new mode in their regional models. E-scooters share similarities with the walk mode in terms of access and convenience, and with the bike mode in terms of speed and range, so many of the recommendations for improved modeling of walk and bike trips will be relevant for e-scooter trips as well.

As regulatory issues are settled, it will become clearer over time where these scooters are allowed to operate (sidewalks, bike paths, bike lanes, in traffic lanes), although this may vary from city to city. It seems (so far) that the e-scooter system operators are willing to share passively collected data on the times and locations of all the trips using their scooters. The availability of such data will be valuable, providing the opportunity to add a new mode with asserted parameters into mode choice models and then calibrate the model parameters to match the data provided by the operators. Over time, as more and more e-scooter trips are collected in household travel surveys, it will be possible to estimate parameters based on survey choice data. Modeling the transportation network company (TNC) mode (Uber, Lyft, etc.) has followed a similar progression over the past two or three years, but in the case of TNCs, the operators have not been willing to share data to use for model calibration.

The role of state DOTs in advancing the state-of-the-practice

The report mentions few examples of DOT models. Most of the recommendations in this report are not relevant to statewide travel models that operate with much larger study areas and larger zones. Nevertheless, many state DOTs have an influence on how the regional, county and local agencies carry out modeling. The influence can be through guidance, model standards/requirements, or availability of funding. Although we learned a bit about this role through our interviews with DOT survey respondents, that was with a small sample. A study focused more on the specific role of DOTs could provide further useful insights.

REFERENCES

Alliance for Biking and Walking. “Bicycling and Walking in the United States 2016: Benchmarking Report”.

Aoun, Alisar, Julie Bjornstad, Brooke DuBose, Meghan Mitman & Mollie Pelon. (2015). 'Bicycle and pedestrian Forecasting Tools: State of the practice.' Washington, DC: Pedestrian and Bicycle Information Center. As of 15 March 2019: http://www.pedbikeinfo.org/cms/downloads/PBIC_WhitePaper_Forecasting.pdf

Bernardin, V and M. Conger (2010). “From Academia to Application: Results from Calibration and Validation of First Hybrid Accessibility-Based Model”. Transportation Research Record 2176(1). pp 50-58. 2010.

Bovy, P.H.L. and M. Bradley (1985). “Route Choice Analyzed with Stated-Preference Approaches”. Transportation Research Record 1037, pp 11-20. 1985.

Bradley, M, J.L. Bowman and B. Griesenbeck (2010) “SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution”. Journal of Choice Modeling. Vol.3(1), pp. 5-31.

Bradley, M., E. Greene and C. Coy (2018). “How Smartphone-Based Household Travel Surveys Will Enable Better Analyses of Travel Behavior”. Presentation at the 18th Conference of the International Association for Travel Behavior Research (IATBR). Santa Barbara, CA. July 2017.

Broach, Joseph, Jennifer Dill & John Gliebe. (2012). 'Where do cyclists ride? A route choice model developed with revealed preference GPS data.' Transportation Research Part A: Policy and Practice 46(10): 1730-40.

Broach, Joseph Paul. (2016). 'Travel mode choice framework incorporating realistic bike and walk routes.' Dissertations and Theses Portland State University (Paper 2702).

Brozen, Madeline, Kate Bridges, Carole Turley Voulgaris & Evelyn Blumenberg. (2017). 'Improving Next Generation of Travel Demand Models to Better Represent Pedestrian Needs: A Case Study of Large California Metropolitan Planning Organizations.' Transportation Research Board 96th Annual Meeting Compendium of Papers.

Brown, B, I. Yamada, K Smith, C. Zick, L. Kowaleski-Jones,and J. Fana (2009). “Mixed land use and walkability: Variations in land use measures and relationships with BMI, overweight, and obesity”. Health Place. 2009 Dec; 15(4): 1130–1141.

Castiglione, J., Hood, J., Freedman, J., Frazier, C., Sun, W. (2014), “Enhancing Active Transportation Sensitivities of an Activity-Based Modeling System,” presented at the 5th Transportation Research Board Conference on Innovations in Travel Modeling, Baltimore, Maryland, Apr. 27-30. http://onlinepubs.trb.org/onlinepubs/conferences/2014/ITM/Presentations/Monday/DynamicModelsDynamicData/jCastiglione.pdf

Clifton, Kelly J., Patrick A. Singleton, Christopher D. Muhs & Robert J. Schneider. (2016). 'Representing pedestrian activity in travel demand models: Framework and application.' Journal of transport geography 52(2016): 111-22.

Cui, Yuchen, & Timothy F. Welch. (2015). 'Estimating Land Use Effects on Bicycle Ridership.' 94th Annual Meeting of the Transportation Research Board.

Dhakar, N., J. Freedman and M. Bradley (2019). “Modeling Bicycle Route Choice and Bike-Transit Mode in Travel Models”. Presented at the 17th TRB Transportation Planning Applications Conference. Portland, OR. June 2019.

Frank LD, Sallis JF, Conway TL, Chapman JE, Saelens BE, Bachman W. (2006). Many pathways from land use to health: Associations between neighborhood walkability and active transportation, body mass index, and air quality. Journal of the American Planning Association. 2006;72(1):75–87.

Griffin, Greg. (2009). “Simple Techniques for Forecasting Bicycle and Pedestrian Demand”. Practicing Planner: Vol. 7(3), 2009.

Halldórsdóttir, Katrín, Otto Anker Nielsen & Carlo Giacomo Prato. 2015. 'Behavioural models for cycling-Case studies of the Copenhagen Region.' Kgs. Lyngby, Copenhagen: Technical University of Denmark.

Hood, J., E Sall, B Charlton (2011), “A GPS-based bicycle route choice model for San Francisco”, California, Transportation Letters: The International Journal of Transportation Research (2011) 3: (63-75).

Hood, J., Erhardt, G., Frazier, C., Schenk, A. (2014), “Estimating Emissions Benefits of Bicycle Facilities with Stand-Alone Software Tools: Incremental Nested Logit Analysis of Bicycle Trips in California’s Monterey Bay Area”, Transportation Research Record 2430, p 124-132.

Jacobsen, P., D. Ragland and C. Komanoff. (2015). “Safety in Numbers for walkers and bicyclists: exploring the machanisms”. Injury Prevention. 2015;21:4 217-220.

Khan, Mobashwir, Kara M Kockelman & Xiaoxia Xiong. (2014). 'Models for anticipating non-motorized travel choices, and the role of the built environment.' Transport Policy 35: 117-26.

Kuzmyak, J. Richard, Jerry Walters, Mark Bradley & Kara M. Kockelman. (2014). 'Estimating bicycling and walking for planning and project development: A guidebook.' Transportation Research Board (NCHRP Project 08-78, Report 770).

Le, HTK, R Buehler and S. Hankey (2018). “Correlates of the Built Environment and Active Travel: Evidence from 20 US Metropolitan Areas”. Environmental Health Perspectives. 2018 July 30;126(7).

Lee, K. and I. Sener. (2017) “Emerging Data Mining for Pedestrian and Bicyclist Monitoring: A Literature Review Report”. Texas Transportation Institute Report UTC Safe-D 01-003, September, 2017.

Li, Siyuan. (2017). 'Cycling in Toronto: Route Choice Behavior and Implications to Infrastructure Planning.' Ontario, Canada: University of Waterloo. As of 15 March 2019: https://uwspace.uwaterloo.ca/bitstream/handle/10012/11250/Li_Siyuan.pdf?sequence=1

Mahmoud, M., Wafic El-Assi, K. Habib & Amer Shalaby. (2015). 'How Active Modes Compete with Motorized Modes in High-Density Areas: A Case Study of Downtown Toronto.' Canadian Transportation Research Forum 50th Annual Conference, Montreal, Quebec.

Maldonado-Hinarejos, Rafael, Aruna Sivakumar & John W. Polak. (2014). 'Exploring the role of individual attitudes and perceptions in predicting the demand for cycling: a hybrid choice modelling approach.' Transportation 41(6): 1287-304.

Mohanty, Sudatta, & Samuel D. Blanchard. (2016). 'Complete Transit: Evaluating Walking and Biking to Transit Using a Mixed Logit Mode Choice Model.' Transportation Research Board 95th Annual Meeting Compendium of Papers (No. 16-2803).

Montini, Lara, Constantinos Antoniou & Kay W. Axhausen. (2017). 'Route and mode choice models using GPS data.' 96th Annual Meeting of the Transportation Research Board 1204: 17-03082.

Muñoz, Begoña, Andres Monzon & Ricardo A. Daziano. (2016). 'The increasing role of latent variables in modelling bicycle mode choice.' Transport Reviews 36(6): 737-71.

Pinjari, Abdul Rawoof, Ram M. Pendyala, Chandra R. Bhat & Paul A. Waddell. (2011). 'Modeling the choice continuum: an integrated model of residential location, auto ownership, bicycle ownership, and commute tour mode choice decisions.' Transportation 38(6): 933.

Proulx, F., and Pozdnukhov, A. (2017). Bicycle Traffic Volume Estimation Using Geographically Weighted Data Fusion. Unpublished, accessible from http://faculty.ce.berkeley.edu/pozdnukhov/papers/Direct_Demand_Fusion_Cycling.pdf

Rosetti, T., C.A. Guevara, P. Galilea and P. Hurtubia (2018). “Modeling safety as a perceptual latent variable to assess cycling infrastructure”. Transportation Research Part A. V.111 (2018) 252-265. Elsevier.

RSG (2018). Mode Choice Model Revisions, Calibration, and Route Level Analysis. Report to the Maricopa Association of Governments (MAG). August, 2018.

RSG (2019). “Impacts 2050 Model Update: New travel models based on longitudinal NHTS data from 1995 to 2017”. Project memorandum for the Delaware Valley Regional Planning Commission (DVRPC). March, 2019.

Semier, C., A. Vest, K. Kingsley, S. Mah, W. Kittleson, C. Sundstrom and K. Brookshire (2016). “Guidebook for Developing Pedestrian and Bicycle Performance Measures”. Report FHWA-HEP-16-037. March 2016.

Sener, Ipek N., Naveen Eluru & Chandra R. Bhat. (2009). 'An analysis of bicycle route choice preferences in Texas, US.' Transportation 36(5): 511-39.

Shen, Qing, Peng Chen, Peter Schmiedeskamp, Alon Bassok & Suzanne Childress. (2014). 'Bicycle Route Choice: GPS Data Collection and Travel Model Development–Year 1 (2012–13).' University of Washington, Seattle: Pacific Northwest Transportation Consortium.

Sidharthan, Raghuprasad, Chandra R. Bhat, Ram M. Pendyala & Konstadinos G. Goulias. (2011). 'Model for children's school travel mode choice: accounting for effects of spatial and social interaction.' Transportation research record 2213(1): 78-86.

Singleton, Patrick A., & Kelly J. Clifton. (2013). 'Pedestrians in regional travel demand forecasting models: State-of-the-practice.' 92nd Annual Meeting of the Transportation Research Board (No. 13-4857).

Stabler, B., M. Bradley, P. Andrews (2017). "Continuous Integration of a Dynamic Multiple Agency Activity-Based Travel Modeling System". Presented at the Transportation Research Board (TRB) 96th Annual Meeting. January 2017.

Stabler, Ben and Jeff Doyle (2017) "Development of a Common Open Platform for Activity-Based Travel Demand Modeling: ActivitySim" TRB Planning Applications Conference. Raleigh, NC, May 2017.

Subhani, A., D. Stephens, R. Kumar & P. Vovsha. (2013). 'Incorporating Cycling in Ottawa-Gatineau Travel Forecasting Model.' 2013 Conference and Exhibition of the Transportation Association of Canada - Transportation: Better-Faster-Safer.

Wardman, Mark, Miles Tight & Matthew Page. (2007). 'Factors influencing the propensity to cycle to work.' Transportation Research Part A: Policy and Practice 41(4): 339-50.

Wei, H., Q. Ai and M. Ramirez-Bernal. (2013). "Bicycle Trip Forecasting Model: Cincinnati Metropolitan Case Study". Final Report to the Ohio Dept. of Transportation Office of Statewide Planning and Research. August, 2013.

Yeboah, Godwin, & Seraphim Alvanides. (2015). 'Route choice analysis of urban cycling behaviors using OpenStreetMap: Evidence from a British urban environment.' In OpenStreetMap in GIScience: Experiences, Research, and Applications, Edited by Jamal Jokar Arsanjani, Alexander Zipf, Peter Mooney & Marco Helbich, 189-210. Springer.

Zephyr (2019). Network Data Standard and Management Tools web page https://zephyrtransport.org/projects/2-network-standard-and-tools/

Zhang, Y. F. Proulx, D. Ragland, R. Schneider and O. Grembek.(2014). "Develop a Plan to Collect Pedestrian Infrastructure and Volume Data for Future Incorporation into Caltrans Accident Surveillance and Analysis System Database". University of California, Berkeley; Report to California Department of Transportation, 2014, 110p.

Zimmermann, Maëlle, Tien Mai & Emma Frejinger. (2017). 'Bike route choice modeling using GPS data without choice sets of paths.' Transportation research part C: emerging technologies 75: 183-96.

Technical Appendix A: Rapid Evidence Review Methodology

Background

The central aim of this task is to undertake a systematic targeted literature search and review of state-of-the-art research on modeling walking and bicycling in regional forecasting models.

Below we set out the search strategy used for the literature review task. This includes:

- where the team will search for literature
- the search terms used
- scope of the literature to be included in the review
- data extraction template and approach to quality assessment.

Literature databases

The search strategies (see below) were implemented in the TRID database by a trained librarian.[7] TRID is arguably the most comprehensive database for transport research that combines the records from TRB's Transportation Research Information Services (TRIS) Database and the OECD's Joint Transport Research Centre's International Transport Research Documentation (ITRD) Database. TRID provides access to more than one million records of transportation research worldwide, including papers from peer-reviewed journals, reports (often referred to as "grey" literature) and conference proceedings.

Defining search terms

Search terms were developed to identify papers that focused on modeling walking and bicycling demand. The search terms were defined to include synonyms for walking and bicycling and multiple word suffixes. They were tested to ensure that they picked up key papers identified by the team.

They are presented below:

(bik* or bicycl* or cycle or bicycling) AND ("route choice" or "mode choice" or "travel demand model*" or forecast*)

(walk or walking or pedestrian*) AND ("route choice" or "mode choice" or "travel demand model*" or forecast*)

(Nonmotori* OR "non-motori*") AND ("route choice" or "mode choice" or "travel demand model* "or forecast*)

[7] The TRID database integrates the content of two major databases, the Organisation for Economic Co-operation and Development's (OECD's) Joint Transport Research Centre's International Transport Research Documentation (ITRD) Database and the US Transportation Research Board's (TRB's) Transportation Research Information Services (TRIS) Database.

Defining inclusion and exclusion criteria

We defined a number of inclusion / exclusion criteria to identify relevant papers. These are summarized in Table A.1.

Table A.1: General Inclusion and exclusion criteria

Criteria	Include
General	
Published in or after 2007	✔
English language, US focus, comparison study with OECD/EU countries	✔
Type of publication/study	
Conference abstract/paper	✔
Journal article – systematic reviews, REAs, quantitative, high-quality observational and qualitative studies	✔
High quality agency reports (e.g. OECD, DfT, EU)	✔
PhD theses	✔
Scope	
Contains information on modeling route choice, mode choice, destination choice	✔
Unimodal models of interest – if provide information that could be used by in multi-modal models	✔
Studies that provide information on relevant explanatory variables, including socio-economic variables, land-use variables, infrastructure variables, environmental variables, as well as perceptions, attitudes and other latent variables	✔
Including walking and bicycling as main modes, as well as access/egress to public transit	✔

Screening of identified literature

Once the results of the full searches were obtained, the titles and abstracts of studies identified from the literature search ('first pass') were screened by a researcher with transport modeling expertise and literature review expertise. A total of 7,834 possible papers were manually reviewed. Given the high number of papers the review was undertaken using a two-stage process. Some papers were eliminated on the basis of the paper title alone, for example a paper titled 'A Revenue Management Slot Allocation Model for Liner Shipping Networks' was identified in the review and could be eliminated based on title alone. For those titles directly or potentially relevant to modeling walk and cycle demand the abstract was reviewed before deciding whether the paper was a candidate for review.

The resulting longlist (40 papers) was saved to an excel sheet, including details of the paper including the title, authors, date and abstract. The sheet also contained the following information on the paper:

- Model response, e.g. route choice, mode choice, etc.
- Walk / cycle, whether the paper is about modeling walking, bicycling or both
- Type of data used for modeling
- Country where the research was conducted.

- RAND assessment of relevant to the project, colored by red (not relevant), amber (possibly relevant) and green (relevant).

The project team reviewed the abstracts and identified 24 papers for review. These reflected a range of topics, including route choice, mode choice and other responses, modeling and guidance papers, and studies both within and outside the US (although the bulk of evidence came from the US). One additional paper was added (PhD research from a student in Denmark).

Table A.2 contains a list of the sources that were reviewed.

Table A.2: Summary of the sources that were reviewed

No.	Paper	Mode	Response	Country
1	Broach, J., et al. (2012). "Where do cyclists ride? A route choice model developed with revealed preference GPS data." Transportation Research Part A: Policy and Practice 46(10): pp 1730-1740.	Cycle	Route	US
2	Broach, J. P., et al. (2016). Travel Mode Choice Framework Incorporating Realistic Bike and Walk Routes: 165p.	Walk and cycle	Mode choice	US
3	Brozen, M., et al. (2017). Improving Next Generation of Travel Demand Models to Better Represent Pedestrian Needs: A Case Study of Large California Metropolitan Planning Organizations.	Walk	Not clear	US
4	Clifton, K. J., et al. (2016). "Representing pedestrian activity in travel demand models: Framework and application." Journal of Transport Geography 52: pp 111-122.	Walk	Generation / mode / destination	US
5	Cui, Y., et al. (2015). Estimating Land Use Effects on Bicycle Ridership.	Cycle	Unimodal bike demand	US
6	Hood, J., et al. (2011). "A GPS-Based Bicycle Route Choice Model for San Francisco, California." Transportation Letters: The International Journal of Transportation Research 3(1): pp 63-75.	Cycle	Route choice	US
7	Khan, M., et al. (2014). "Models for anticipating non-motorized travel choices, and the role of the built environment." Transport Policy 35: pp 117-126.	Walk and cycle	Generation / mode / destination	US
8	Kuzmyak, J. R., et al. (2014). Estimating Bicycling and Walking for Planning and Project Development: A Guidebook, Transportation Research Board NCHRP Report 770: 161p.	Walk and cycle	Generation / mode / destination	US
9	Li, S., et al. (2017). bicycling in Toronto: Route Choice Behavior and Implications to Infrastructure Planning.	Cycle	Route	Canada
10	Mahmoud, M. S., et al. (2015). How Active Modes Compete with Motorized Modes in High-Density Areas: A Case Study of Downtown Toronto.	Walk and cycle	Mode choice	Canada
11	Maldonado-Hinarejos, R., et al. (2014). Exploring the Role of Individual Attitudes and Perceptions in Predicting the Demand for bicycling: A Hybrid Choice Modeling Approach.	Cycle	Mode choice	TBC
12	Mohanty, S., et al. (2016). Complete Transit: Evaluating Walking and Biking to Transit Using a Mixed Logit Mode Choice Model.	Walk and cycle	Access to transit	US
13	Montini, L., et al. (2017). Route and Mode Choice Models Using GPS Data.	Walk and cycle	Route / mode choice	Switzerl and
14	Muñoz, B., et al. (2016). "The Increasing Role of Latent Variables in Modeling Bicycle Mode Choice." Transport Reviews 36(6): pp 737-771.	Cycle	TBC	TBC
15	Pinjari, A. R., et al. (2011). "Modeling the Choice Continuum: An Integrated Model of Residential Location, Auto Ownership, Bicycle Ownership, and Commute Tour Mode Choice Decisions." Transportation 38(6): pp 933-958.	Walk and cycle	residential location / auto / bike ownership / mode choice	US
16	Sener, I. N., et al. (2010). An Analysis of Bicycle Route Choice Preferences in Texas, U.S.	Cycle	Route choice	US
17	Shen, Q., et al. (2014). Bicycle Route Choice: GPS Data Collection and Travel Model Development: 71p.	Cycle	Route choice	US
18	Sidharthan, R., et al. (2011). "Model for Children's School Travel Mode Choice: Accounting for Effects of Spatial and Social Interaction." Transportation Research Record: Journal of the Transportation Research Board(2213): pp 78-86.	Walk and cycle	School mode choice	US
19	Singleton, P. A., et al. (2013). Pedestrians in Regional Travel Demand Forecasting Models: State of the Practice.	Walk and cycle	TBC	US
20	Subhani, A., et al. (2013). Incorporating bicycling in Ottawa-Gatineau Travel Forecasting Model.	Cycle	Route	Canada
21	Wardman, M., et al. (2007). "Factors Influencing the Propensity to Cycle to Work." Transportation Research Part A: Policy and Practice 41(4): pp 339-350.	Cycle	Mode choice (commute)	UK

No.	Paper	Mode	Response	Country
22	Yeboah, G., et al. (2015). "Route Choice Analysis of Urban bicycling Behaviors Using OpenStreetMap: Evidence from a British Urban Environment." Lecture Notes in Geoinformation and Cartography: pp 189-210.	Cycle	Route choice	UK
23	Zimmermann, M., et al. (2017). "Bike route choice modeling using GPS data without choice sets of paths." Transportation Research Part C: Emerging Technologies 75: pp 183-196.	Cycle	Route choice	UK
24	Aoun, A., J. Bjornstad, B. DuBose, M. Mitman and M. Pelon, Fehr & Peers (2015) Bicycle and Pedestrian Forecasting Tools: State of the Practice, FHWA White Paper	Walk and cycle	Route choice / mode choice / trip generation	US
25	Halldórsdóttir, K. (2015) Behavioral Models for bicycling - Case Studies of the Copenhagen Region, Technical University of Denmark (Phd thesis).	Cycle	Route & mode choice / access/egress to train stations	Denmark

Note: We were unable to access the Brozen et al. (2017) paper, but we did find report that the paper is based on (Blumenberg et al. . Heightening Walking above its Pedestrian Status: Walking and Travel Behavior in California, University of California Center for Economic Competitiveness in Transportation). There is very little discussion of travel demand modelling in the report and therefore we proposed to exclude this paper from the review.

Data extraction

An Excel data extraction spreadsheet was developed to support data collection. This provided an efficient, systematic tool for consolidating all relevant information drawn from the selected studies and enabled the team to organize data from different studies in a comprehensible way that facilitated synthesis and comparison. Information collected in the extraction sheet included:

- Study number (our number)
  - Authors
  - Date of publication
  - Journal
- Reviewer
- Study location / country
- Mode of interest: bicycle, walk or both
- Evidence type
  - Model
  - Review
  - Other
- Geography
  - Urban
  - Rural
  - Regional
  - National
  - Other
- Level of geographical detail
- Model response
  - Route choice
  - Mode choice
  - Trip / tour generation

  - Other, to be specified

- Model type
  - Aggregate or disaggregate model, details as necessary
  - Trip-model
  - Tour-based model
  - Activity-based model
  - Other, to be specified

- Purpose
  - Commute
  - Business
  - Utilitarian
  - School
  - Other, to be specified

- Data type and sample size
  - Household survey data
  - Other RP data, with brief description
  - GPS data
  - SP data
  - Other, to be described

- Sample size, if reported
- Dependent variable
- Explanatory variables, separately for:
  - Infrastructure / network
  - Socioeconomic variables
  - Land-use / built environment
  - Environment, e.g. topography and weather
  - Attitudes / Perceptions
  - Other, to be described

- Quality assessment of research
- Summary of findings
- Lessons for guidance

All reviewers reviewed one paper to ensure consistency in the review approach.

Technical Appendix B: Detailed Responses from the On-line Survey of MPO and DOT Modelers

In this section, we provide a listing of many tabulations provided on the survey data. The tabulations are provided in three main groups:

- Tables Section A: Segmentation by MPOs vs DOTs
- Tables Section B: Segmentation by Bike/Walk Model vs. No Current Bike/Walk Model
- Tables Section C: Segmentation by Status or Interest in Adopting an Activity-Based Model

Sections B and C also show a breakdown of the segments according to the classification questions asked for MPOs and DOTs, in terms of both column percentages and row percentages.

Tables Section A: Segmentation by MPOs vs DOTs

Segmentation Variable

		Frequency	Percent
Is your agency a regional MPO or state DOT?	Regional MPO	72	75.0
	State DOT	24	25.0
	Total	96	100.0

Crosstabs by MPO vs DOT

		Regional MPO	State DOT
Does your agency currently use a model to study/forecast bicycle or pedestrian trip demand in your region?	Yes, both bicycle and pedestrian trip demand, as separate modes	34.7%	16.7%
	Yes, bicycle and pedestrian trip demand, grouped as a single “non-motorized” mode	19.4%	8.3%
	Yes, bicycle trip demand, but not pedestrian trip demand	4.2%	
	No, neither	41.7%	75.0%
Total	Total	100.0%	100.0%

For what reasons does you agency use a model (If do not use a model, coded as "no" below)

		Regional MPO	State DOT
Modeling for regional program evaluation	yes	52.8%	12.5%
	no	47.2%	87.5%
Total		100.0%	100.0%

		Regional MPO	State DOT
Modeling for local program evaluation	yes	23.6%	4.2%
	no	76.4%	95.8%
Total		100.0%	100.0%

		Regional MPO	State DOT
Modeling for traffic safety evaluation	yes	8.3%	4.2%
	no	91.7%	95.8%
Total		100.0%	100.0%

		Regional MPO	State DOT
Modeling for active transportation health benefit evaluation	**yes**	**20.8%**	**4.2%**
	no	**79.2%**	**95.8%**
Total		**100.0%**	**100.0%**

		Regional MPO	State DOT
Modeling for social equity evaluation	**yes**	**19.4%**	**4.2%**
	no	**80.6%**	**95.8%**
Total		**100.0%**	**100.0%**

		Regional MPO	State DOT
Other reasons (please specify)	**yes**	**6.9%**	**12.5%**
	no	**93.1%**	**87.5%**
Total		**100.0%**	**100.0%**

Which bicycle modeling approaches do you currently use or are interested in adopting?

(Note: This question is specifically for modeling bicycle trips. A separate question for modeling pedestrian trips follows this one.)

		Regional MPO	State DOT
Bike trips predicted from an activity-based or tour-based model	Currently use	19.7%	13.0%
	Currently developing for future use	3.0%	8.7%
	Plan to develop in the next 1-2 years	4.5%	4.3%
	Interested in developing, but not currently planned	33.3%	13.0%
	No plan to develop	31.8%	56.5%
	Do not know	7.6%	4.3%
	Total	100.0%	100.0%

		Regional MPO	State DOT
Bike trips predicted from a trip-based model	Currently use	31.8%	4.3%
	Currently developing for future use		13.0%
	Plan to develop in the next 1-2 years	1.5%	
	Interested in developing, but not currently planned	31.8%	34.8%
	No plan to develop	28.8%	39.1%
	Do not know	6.1%	8.7%
Total		100.0%	100.0%

		Regional MPO	State DOT
Bike trips predicted from a bike-specific direct demand model	Currently use	9.7%	
	Plan to develop in the next 1-2 years	1.6%	
	Interested in developing, but not currently planned	33.9%	29.2%
	No plan to develop	46.8%	58.3%
	Do not know	8.1%	12.5%
Total		100.0%	100.0%

		Regional MPO	State DOT
Transferring findings from bike route choice models	Currently use	9.5%	
	Plan to develop in the next 1-2 years	1.6%	4.3%
	Interested in developing, but not currently planned	41.3%	13.0%
	No plan to develop	34.9%	65.2%
	Do not know	12.7%	17.4%
Total		100.0%	100.0%

		Regional MPO	State DOT
Assigning bicycle trips to a network	Currently use	15.6%	4.3%
	Currently developing for future use	3.1%	4.3%
	Plan to develop in the next 1-2 years	4.7%	4.3%
	Interested in developing, but not currently planned	53.1%	30.4%
	No plan to develop	17.2%	52.2%
	Do not know	6.3%	4.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Modeling bike access to transit	Currently use	3.1%	4.5%
	Currently developing for future use	3.1%	
	Plan to develop in the next 1-2 years	4.6%	
	Interested in developing, but not currently planned	63.1%	50.0%
	No plan to develop	18.5%	40.9%
	Do not know	7.7%	4.5%
Total		100.0%	100.0%

		Regional MPO	State DOT
Collection/use of bicycle count data	Currently use	44.3%	33.3%
	Currently developing for future use	14.3%	8.3%
	Plan to develop in the next 1-2 years	11.4%	8.3%
	Interested in developing, but not currently planned	20.0%	20.8%
	No plan to develop	5.7%	20.8%
	Do not know	4.3%	8.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Collection/use of bicyclist intercept/O-D survey data	Currently use	9.1%	4.3%
	Plan to develop in the next 1-2 years	12.1%	8.7%
	Interested in developing, but not currently planned	42.4%	43.5%
	No plan to develop	25.8%	30.4%
	Do not know	10.6%	13.0%
Total		100.0%	100.0%

		Regional MPO	State DOT
Collection/use of GPS data specific to bicycle trips	Currently use	9.1%	12.5%
	Currently developing for future use	3.0%	8.3%
	Plan to develop in the next 1-2 years	13.6%	8.3%
	Interested in developing, but not currently planned	47.0%	33.3%
	No plan to develop	18.2%	29.2%
	Do not know	9.1%	8.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Use of an all-streets network	Currently use	18.5%	8.7%
	Currently developing for future use	7.7%	13.0%
	Plan to develop in the next 1-2 years	4.6%	8.7%
	Interested in developing, but not currently planned	27.7%	17.4%
	No plan to develop	24.6%	30.4%
	Do not know	16.9%	21.7%
Total		100.0%	100.0%

		Regional MPO	State DOT
Use of OpenStreetMap data and/or tools	Currently use	9.5%	4.3%
	Currently developing for future use	7.9%	8.7%
	Plan to develop in the next 1-2 years	3.2%	13.0%
	Interested in developing, but not currently planned	20.6%	21.7%
	No plan to develop	42.9%	34.8%
	Do not know	15.9%	17.4%
Total		100.0%	100.0%

		Regional MPO	State DOT
Use of microzone-level detail (e.g. census blocks or parcels) in model	Currently use	10.8%	16.7%
	Currently developing for future use	12.3%	8.3%
	Plan to develop in the next 1-2 years	4.6%	4.2%
	Interested in developing, but not currently planned	24.6%	25.0%
	No plan to develop	35.4%	33.3%
	Do not know	12.3%	12.5%
Total		100.0%	100.0%

Which pedestrian-related data types and collection methods do you currently use or are interested in adopting?

		Regional MPO	State DOT
Walk trips predicted from an activity-based or tour-based model	Currently use	19.4%	17.4%
	Currently developing for future use	4.5%	4.3%
	Plan to develop in the next 1-2 years	4.5%	4.3%
	Interested in developing, but not currently planned	26.9%	13.0%
	No plan to develop	34.3%	56.5%
	Do not know	10.4%	4.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Walk trips predicted from a trip-based model	Currently use	37.9%	8.7%
	Currently developing for future use		13.0%
	Plan to develop in the next 1-2 years	1.5%	
	Interested in developing, but not currently planned	24.2%	21.7%
	No plan to develop	27.3%	43.5%
	Do not know	9.1%	13.0%
Total		100.0%	100.0%

		Regional MPO	State DOT
Walk trips predicted from a mode-specific direct demand model	Currently use	12.7%	
	Plan to develop in the next 1-2 years	1.6%	
	Interested in developing, but not currently planned	28.6%	30.4%
	No plan to develop	47.6%	60.9%
	Do not know	9.5%	8.7%
Total		100.0%	100.0%

		Regional MPO	State DOT
Transferring findings from pedestrian route choice models	Currently use	1.6%	
	Interested in developing, but not currently planned	39.3%	21.7%
	No plan to develop	47.5%	65.2%
	Do not know	11.5%	13.0%
Total		100.0%	100.0%

		Regional MPO	State DOT
Assigning walk trips to a network	Currently use	7.8%	8.7%
	Plan to develop in the next 1-2 years	4.7%	
	Interested in developing, but not currently planned	40.6%	26.1%
	No plan to develop	40.6%	60.9%
	Do not know	6.3%	4.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Detailed modeling of transit walk access and egress trips	Currently use	20.9%	4.2%
	Currently developing for future use	3.0%	
	Plan to develop in the next 1-2 years	4.5%	
	Interested in developing, but not currently planned	40.3%	50.0%
	No plan to develop	23.9%	41.7%
	Do not know	7.5%	4.2%
Total		100.0%	100.0%

		Regional MPO	State DOT
Collection/use of pedestrian count data	Currently use	28.2%	26.1%
	Currently developing for future use	8.5%	4.3%
	Plan to develop in the next 1-2 years	9.9%	4.3%
	Interested in developing, but not currently planned	35.2%	30.4%
	No plan to develop	9.9%	26.1%
	Do not know	8.5%	8.7%
Total		100.0%	100.0%

		Regional MPO	State DOT
Collection/use of pedestrian intercept/O-D survey data	Currently use	8.8%	4.3%
	Currently developing for future use	2.9%	
	Plan to develop in the next 1-2 years	5.9%	4.3%
	Interested in developing, but not currently planned	42.6%	39.1%
	No plan to develop	30.9%	39.1%
	Do not know	8.8%	13.0%
Total		100.0%	100.0%

		Regional MPO	State DOT
Collection/use of GPS data specific to pedestrian trips	Currently use	4.5%	8.3%
	Currently developing for future use	7.5%	8.3%
	Plan to develop in the next 1-2 years	9.0%	4.2%
	Interested in developing, but not currently planned	40.3%	29.2%
	No plan to develop	28.4%	41.7%
	Do not know	10.4%	8.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Use of an all-streets network	Currently use	20.9%	8.7%
	Currently developing for future use	6.0%	8.7%
	Plan to develop in the next 1-2 years	3.0%	8.7%
	Interested in developing, but not currently planned	25.4%	21.7%
	No plan to develop	31.3%	34.8%
	Do not know	13.4%	17.4%
Total		100.0%	100.0%

		Regional MPO	State DOT
Use of OpenStreetMap data and/or tools	Currently use	3.1%	4.3%
	Currently developing for future use	6.2%	8.7%
	Plan to develop in the next 1-2 years	6.2%	4.3%
	Interested in developing, but not currently planned	26.2%	26.1%
	No plan to develop	44.6%	34.8%
	Do not know	13.8%	21.7%
Total		100.0%	100.0%

		Regional MPO	State DOT
Use of microzone-level detail (e.g. census blocks or parcels) in model	Currently use	12.1%	16.7%
	Currently developing for future use	7.6%	4.2%
	Plan to develop in the next 1-2 years	3.0%	8.3%
	Interested in developing, but not currently planned	28.8%	25.0%
	No plan to develop	37.9%	37.5%
	Do not know	10.6%	8.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Are there any bicycle or pedestrian modeling approaches or data types your agency is using that were not listed in the preceding questions? (Please specify)	No	91.4%	95.7%
	Yes, bicycle-related	1.4%	
	Yes, pedestrian-related	2.9%	
	Yes, bicycle- and pedestrian-related	4.3%	4.3%
Total		100.0%	100.0%

How important are the following issues as impediments to your agency's development of tools or approaches for modeling bicycle and/or pedestrian demand?

		Regional MPO	State DOT
Availability of staff time	Very important	65.7%	50.0%
	Somewhat important	28.6%	37.5%
	Not very important	2.9%	8.3%
	Not important at all	1.4%	4.2%
	Not applicable/do not know	1.4%	
Total		100.0%	100.0%

		Regional MPO	State DOT
Level of staff training	Very important	40.0%	33.3%
	Somewhat important	30.0%	37.5%
	Not very important	21.4%	29.2%
	Not important at all	5.7%	
	Not applicable/do not know	2.9%	
Total		100.0%	100.0%

		Regional MPO	State DOT
Funding for staff and/or consultant time	Very important	58.6%	41.7%
	Somewhat important	25.7%	41.7%
	Not very important	12.9%	12.5%
	Not important at all	1.4%	4.2%
	Not applicable/do not know	1.4%	
Total		100.0%	100.0%

		Regional MPO	State DOT
Funding for computing resources	Very important	28.2%	20.8%
	Somewhat important	25.4%	25.0%
	Not very important	35.2%	41.7%
	Not important at all	7.0%	12.5%
	Not applicable/do not know	4.2%	
Total		100.0%	100.0%

		Regional MPO	State DOT
Funding for data collection and/or acquisition	Very important	57.7%	41.7%
	Somewhat important	35.2%	45.8%
	Not very important	4.2%	12.5%
	Not important at all	1.4%	
	Not applicable/do not know	1.4%	
Total		100.0%	100.0%

		Regional MPO	State DOT
Lack of agency consensus on modeling/research priorities	Very important	12.9%	25.0%
	Somewhat important	27.1%	16.7%
	Not very important	41.4%	33.3%
	Not important at all	11.4%	20.8%
	Not applicable/do not know	7.1%	4.2%
Total		100.0%	100.0%

		Regional MPO	State DOT
Lack of clear guidance from the modeling/research community	Very important	19.7%	20.8%
	Somewhat important	38.0%	29.2%
	Not very important	21.1%	29.2%
	Not important at all	12.7%	12.5%
	Not applicable/do not know	8.5%	8.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Lack of training courses or seminars directly related to modeling bike/pedestrian demand	Very important	23.9%	12.5%
	Somewhat important	35.2%	41.7%
	Not very important	25.4%	25.0%
	Not important at all	7.0%	12.5%
	Not applicable/do not know	8.5%	8.3%
Total		100.0%	100.0%

		Regional MPO	State DOT
Are there any impediments that your agency faces that were not listed in the previous questions?	Yes (Please provide a brief description)	20.0%	16.7%
	No	80.0%	83.3%
Total		100.0%	100.0%

Tables Section B: Segmentation by Bike/Walk Model vs. No Current Bike/Walk Model

Segmentation Variable

		Frequency	Percent
Currently use a model to study/forecast bicycle or pedestrian demand? (Derived variable)	Models bike/ped	48	50.0
	No model bike/ped	48	50.0
	Total	96	100.0

Crosstabs by model vs no model

		Models bike/ped	No model bike/ped
Does your agency currently use a model to study/forecast bicycle or pedestrian trip demand in your region?	Yes, both bicycle and pedestrian trip demand, as separate modes	60.4%	
	Yes, bicycle and pedestrian trip demand, grouped as a single “non-motorized” mode	33.3%	
	Yes, bicycle trip demand, but not pedestrian trip demand	6.3%	
	No, neither		100.0%
Total		100.0%	100.0%

For what reasons does you agency use a model (If do not use a model, coded as "no" below)

		Models bike/ped	No model bike/ped
Modeling for regional program evaluation	yes	85.4%	
	no	14.6%	100.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Modeling for local program evaluation	yes	37.5%	
	no	62.5%	100.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Modeling for traffic safety evaluation	yes	14.6%	
	no	85.4%	100.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Modeling for active transportation health benefit evaluation	yes	33.3%	
	no	66.7%	100.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Modeling for social equity evaluation	yes	31.3%	
	no	68.8%	100.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Other reasons	yes	16.7%	
	no	83.3%	100.0%
Total		100.0%	100.0%

Which bicycle modeling approaches do you currently use or are interested in adopting? (Note: This question is specifically for modeling bicycle trips. A separate question for modeling pedestrian trips follows this one.)

		Models bike/ped	No model bike/ped
Bike trips predicted from an activity-based or tour-based model	Currently use	36.4%	
	Currently developing for future use	9.1%	
	Plan to develop in the next 1-2 years	4.5%	4.4%
	Interested in developing, but not currently planned	22.7%	33.3%
	No plan to develop	27.3%	48.9%
	Do not know		13.3%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Bike trips predicted from a trip-based model	Currently use	50.0%	
	Currently developing for future use		6.7%
	Plan to develop in the next 1-2 years	2.3%	
	Interested in developing, but not currently planned	18.2%	46.7%
	No plan to develop	29.5%	33.3%
	Do not know		13.3%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Bike trips predicted from a bike-specific direct demand model	Currently use	15.4%	
	Plan to develop in the next 1-2 years	2.6%	
	Interested in developing, but not currently planned	20.5%	42.6%
	No plan to develop	56.4%	44.7%
	Do not know	5.1%	12.8%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Transferring findings from bike route choice models	Currently use	14.6%	
	Plan to develop in the next 1-2 years	2.4%	2.2%
	Interested in developing, but not currently planned	29.3%	37.8%
	No plan to develop	43.9%	42.2%
	Do not know	9.8%	17.8%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Assigning bicycle trips to a network	Currently use	26.2%	
	Currently developing for future use	7.1%	
	Plan to develop in the next 1-2 years	7.1%	2.2%
	Interested in developing, but not currently planned	47.6%	46.7%
	No plan to develop	11.9%	40.0%
	Do not know		11.1%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Modeling bike access to transit	Currently use	4.8%	2.2%
	Currently developing for future use	4.8%	
	Plan to develop in the next 1-2 years	4.8%	2.2%
	Interested in developing, but not currently planned	64.3%	55.6%
	No plan to develop	16.7%	31.1%
	Do not know	4.8%	8.9%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Collection/use of bicycle count data	Currently use	51.1%	31.9%
	Currently developing for future use	12.8%	12.8%
	Plan to develop in the next 1-2 years	6.4%	14.9%
	Interested in developing, but not currently planned	21.3%	19.1%
	No plan to develop	4.3%	14.9%
	Do not know	4.3%	6.4%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Collection/use of bicyclist intercept/O-D survey data	Currently use	13.6%	2.2%
	Plan to develop in the next 1-2 years	6.8%	15.6%
	Interested in developing, but not currently planned	52.3%	33.3%
	No plan to develop	18.2%	35.6%
	Do not know	9.1%	13.3%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Collection/use of GPS data specific to bicycle trips	Currently use	11.6%	8.5%
	Currently developing for future use	2.3%	6.4%
	Plan to develop in the next 1-2 years	11.6%	12.8%
	Interested in developing, but not currently planned	51.2%	36.2%
	No plan to develop	16.3%	25.5%
	Do not know	7.0%	10.6%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Use of an all-streets network	Currently use	25.6%	6.7%
	Currently developing for future use	11.6%	6.7%
	Plan to develop in the next 1-2 years	4.7%	6.7%
	Interested in developing, but not currently planned	20.9%	28.9%
	No plan to develop	20.9%	31.1%
	Do not know	16.3%	20.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Use of OpenStreetMap data and/or tools	Currently use	4.8%	11.4%
	Currently developing for future use	11.9%	4.5%
	Plan to develop in the next 1-2 years	4.8%	6.8%
	Interested in developing, but not currently planned	14.3%	27.3%
	No plan to develop	45.2%	36.4%
	Do not know	19.0%	13.6%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Use of microzone-level detail (e.g. census blocks or parcels) in model	Currently use	14.0%	10.9%
	Currently developing for future use	20.9%	2.2%
	Plan to develop in the next 1-2 years	2.3%	6.5%
	Interested in developing, but not currently planned	20.9%	28.3%
	No plan to develop	34.9%	34.8%
	Do not know	7.0%	17.4%
Total		100.0%	100.0%

Which pedestrian-related data types and collection methods do you currently use or are interested in adopting?

		Models bike/ped	No model bike/ped
Walk trips predicted from an activity-based or tour-based model	Currently use	37.8%	
	Currently developing for future use	8.9%	
	Plan to develop in the next 1-2 years	4.4%	4.4%
	Interested in developing, but not currently planned	17.8%	28.9%
	No plan to develop	28.9%	51.1%
	Do not know	2.2%	15.6%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Walk trips predicted from a trip-based model	Currently use	59.1%	2.2%
	Currently developing for future use		6.7%
	Plan to develop in the next 1-2 years	2.3%	
	Interested in developing, but not currently planned	6.8%	40.0%
	No plan to develop	29.5%	33.3%
	Do not know	2.3%	17.8%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Walk trips predicted from a mode-specific direct demand model	Currently use	20.0%	
	Plan to develop in the next 1-2 years		2.2%
	Interested in developing, but not currently planned	12.5%	43.5%
	No plan to develop	62.5%	41.3%
	Do not know	5.0%	13.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Transferring findings from pedestrian route choice models	Currently use	2.5%	
	Interested in developing, but not currently planned	32.5%	36.4%
	No plan to develop	55.0%	50.0%
	Do not know	10.0%	13.6%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Assigning walk trips to a network	Currently use	16.7%	
	Plan to develop in the next 1-2 years	4.8%	2.2%
	Interested in developing, but not currently planned	33.3%	40.0%
	No plan to develop	45.2%	46.7%
	Do not know		11.1%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Detailed modeling of transit walk access and egress trips	Currently use	29.5%	4.3%
	Currently developing for future use	4.5%	
	Plan to develop in the next 1-2 years	4.5%	2.1%
	Interested in developing, but not currently planned	34.1%	51.1%
	No plan to develop	22.7%	34.0%
	Do not know	4.5%	8.5%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Collection/use of pedestrian count data	Currently use	33.3%	21.7%
	Currently developing for future use	6.3%	8.7%
	Plan to develop in the next 1-2 years	6.3%	10.9%
	Interested in developing, but not currently planned	35.4%	32.6%
	No plan to develop	10.4%	17.4%
	Do not know	8.3%	8.7%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Collection/use of pedestrian intercept/O-D survey data	Currently use	15.2%	
	Currently developing for future use	4.3%	
	Plan to develop in the next 1-2 years	2.2%	8.9%
	Interested in developing, but not currently planned	45.7%	37.8%
	No plan to develop	26.1%	40.0%
	Do not know	6.5%	13.3%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Collection/use of GPS data specific to pedestrian trips	Currently use	6.7%	4.3%
	Currently developing for future use	11.1%	4.3%
	Plan to develop in the next 1-2 years	6.7%	8.7%
	Interested in developing, but not currently planned	35.6%	39.1%
	No plan to develop	31.1%	32.6%
	Do not know	8.9%	10.9%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Use of an all-streets network	Currently use	26.7%	8.9%
	Currently developing for future use	8.9%	4.4%
	Plan to develop in the next 1-2 years	4.4%	4.4%
	Interested in developing, but not currently planned	17.8%	31.1%
	No plan to develop	28.9%	35.6%
	Do not know	13.3%	15.6%
Total		100.0%	100.0%

Use of OpenStreetMap data and/or tools * Models bike or ped demand? (recode from Q1) Crosstabulation

		Models bike/ped	No model bike/ped
Use of OpenStreetMap data and/or tools	Currently use		6.7%
	Currently developing for future use	9.3%	4.4%
	Plan to develop in the next 1-2 years	9.3%	2.2%
	Interested in developing, but not currently planned	16.3%	35.6%
	No plan to develop	48.8%	35.6%
	Do not know	16.3%	15.6%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Use of microzone-level detail (e.g. census blocks or parcels) in model	Currently use	15.9%	10.9%
	Currently developing for future use	13.6%	
	Plan to develop in the next 1-2 years	4.5%	4.3%
	Interested in developing, but not currently planned	20.5%	34.8%
	No plan to develop	36.4%	39.1%
	Do not know	9.1%	10.9%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Are there any bicycle or pedestrian modeling approaches or data types your agency is using that were not listed in the preceding questions?	No	85.1%	100.0%
	Yes, bicycle-related	2.1%	
	Yes, pedestrian-related	4.3%	
	Yes, bicycle- and pedestrian-related	8.5%	
Total		100.0%	100.0%

How important are the following issues as impediments to your agency's development of tools or approaches for modeling bicycle and/or pedestrian demand?

		Models bike/ped	No model bike/ped
Availability of staff time	Very important	70.2%	53.2%
	Somewhat important	27.7%	34.0%
	Not very important		8.5%
	Not important at all	2.1%	2.1%
	Not applicable/do not know		2.1%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Level of staff training	Very important	40.4%	36.2%
	Somewhat important	29.8%	34.0%
	Not very important	23.4%	23.4%
	Not important at all	6.4%	2.1%
	Not applicable/do not know		4.3%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Funding for staff and/or consultant time	Very important	66.0%	42.6%
	Somewhat important	25.5%	34.0%
	Not very important	6.4%	19.1%
	Not important at all	2.1%	2.1%
	Not applicable/do not know		2.1%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Funding for computing resources	Very important	31.3%	21.3%
	Somewhat important	20.8%	29.8%
	Not very important	35.4%	38.3%
	Not important at all	10.4%	6.4%
	Not applicable/do not know	2.1%	4.3%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Funding for data collection and/or acquisition	Very important	58.3%	48.9%
	Somewhat important	41.7%	34.0%
	Not very important		12.8%
	Not important at all		2.1%
	Not applicable/do not know		2.1%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Lack of agency consensus on modeling/research priorities	Very important	10.6%	21.3%
	Somewhat important	29.8%	19.1%
	Not very important	42.6%	36.2%
	Not important at all	14.9%	12.8%
	Not applicable/do not know	2.1%	10.6%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Lack of clear guidance from the modeling/research community	Very important	18.8%	21.3%
	Somewhat important	37.5%	34.0%
	Not very important	22.9%	23.4%
	Not important at all	16.7%	8.5%
	Not applicable/do not know	4.2%	12.8%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Lack of training courses or seminars directly related to modeling bike/pedestrian demand	Very important	18.8%	23.4%
	Somewhat important	33.3%	40.4%
	Not very important	35.4%	14.9%
	Not important at all	8.3%	8.5%
	Not applicable/do not know	4.2%	12.8%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
Are there any impediments that your agency faces in modeling bicycle and/or pedestrian travel demand that were not listed in the previous questions?	Yes (Please provide a brief description)	16.7%	21.7%
	No	83.3%	78.3%
Total		100.0%	100.0%

Classification questions as column percentages

		Models bike/ped	No model bike/ped
Is your agency a regional MPO or state DOT?	Regional MPO	87.5%	62.5%
	State DOT	12.5%	37.5%
Total		100.0%	100.0%

Classification questions for State DOT respondents

		Models bike/ped	No model bike/ped
How many travel modeling staff does your agency have?	0-2	50.0%	33.3%
	3-4	16.7%	22.2%
	5-9	16.7%	44.4%
	10 or more	16.7%	
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
What is the population of your state?	Less than 1.5 million		5.6%
	1.5 million to 3.5 million	33.3%	27.8%
	3.5 million to 5.5 million	33.3%	
	5.5 million to 8 million		16.7%
	Over 8 million	33.3%	50.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
What is your state's bike mode share for commute trips?	0-0.5%	40.0%	44.4%
	0.5-1%	20.0%	16.7%
	1% or greater	20.0%	5.6%
	Don't know	20.0%	33.3%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
What is your state's walk mode share for commute trips?	0-1%	60.0%	33.3%
	1-3%		22.2%
	3% or greater	20.0%	11.1%
	Don't know	20.0%	33.3%
Total		100.0%	100.0%

Classification questions for Regional MPO respondents

		Models bike/ped	No model bike/ped
How many travel modeling staff does your agency have?	None	2.4%	37.9%
	1-2	52.4%	58.6%
	3-4	21.4%	3.4%
	5 or more	23.8%	
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
What is the population of your region?	Less than 250,000	19.0%	46.4%
	250,000 to 500,000	16.7%	21.4%
	500,000 to 1 million	19.0%	17.9%
	1 million to 2.5 million	16.7%	3.6%
	2.5 million to 5 million	11.9%	10.7%
	Over 5 million	16.7%	
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
What is your region's bike mode share for commute trips?	0-1%	38.1%	57.1%
	1-3%	38.1%	17.9%
	3% or greater	16.7%	
	Don't know	7.1%	25.0%
Total		100.0%	100.0%

		Models bike/ped	No model bike/ped
What is your region's walk mode share for commute trips?	0-1%	11.9%	21.4%
	1-4%	54.8%	46.4%
	4% or greater	26.2%	3.6%
	Don't know	7.1%	28.6%
Total		100.0%	100.0%

Classification questions as row percentages

		Models bike/ped	No model bike/ped	
Is your agency a regional MPO or state DOT?	Regional MPO	58.3%	41.7%	100.0%
	State DOT	25.0%	75.0%	100.0%

		Models bike/ped	No model bike/ped	
How many travel modeling staff does your agency have?	0-2	33.3%	66.7%	100.0%
	3-4	20.0%	80.0%	100.0%
	5-9	11.1%	88.9%	100.0%
	10 or more	100.0%		100.0%

		Models bike/ped	No model bike/ped	
What is the population of your state?	Less than 1.5 million		100.0%	100.0%
	1.5 million to 3.5 million	28.6%	71.4%	100.0%
	3.5 million to 5.5 million	100.0%		100.0%
	5.5 million to 8 million		100.0%	100.0%
	Over 8 million	18.2%	81.8%	100.0%

		Models bike/ped	No model bike/ped	
What is your state's bike mode share for commute trips?	0-0.5%	20.0%	80.0%	100.0%
	0.5-1%	25.0%	75.0%	100.0%
	1% or greater	50.0%	50.0%	100.0%
	Don't know	14.3%	85.7%	100.0%

		Models bike/ped	No model bike/ped	
What is your state's walk mode share for commute trips?	0-1%	33.3%	66.7%	100.0%
	1-3%		100.0%	100.0%
	3% or greater	33.3%	66.7%	100.0%
	Don't know	14.3%	85.7%	100.0%

		Models bike/ped	No model bike/ped	
How many travel modeling staff does your agency have?	None	8.3%	91.7%	100.0%
	1-2	56.4%	43.6%	100.0%
	3-4	90.0%	10.0%	100.0%
	5 or more	100.0%		100.0%

		Models bike/ped	No model bike/ped	
What is the population of your region?	Less than 250,000	38.1%	61.9%	100.0%
	250,000 to 500,000	53.8%	46.2%	100.0%
	500,000 to 1 million	61.5%	38.5%	100.0%
	1 million to 2.5 million	87.5%	12.5%	100.0%
	2.5 million to 5 million	62.5%	37.5%	100.0%
	Over 5 million	100.0%		100.0%

		Models bike/ped	No model bike/ped	
What is your region's bike mode share for commute trips?	0-1%	50.0%	50.0%	100.0%
	1-3%	76.2%	23.8%	100.0%
	3% or greater	100.0%		100.0%
	Don't know	30.0%	70.0%	100.0%

		Models bike/ped	No model bike/ped	
What is your region's walk mode share for commute trips?	0-1%	45.5%	54.5%	100.0%
	1-4%	63.9%	36.1%	100.0%
	4% or greater	91.7%	8.3%	100.0%
	Don't know	27.3%	72.7%	100.0%

Tables Section C: Segmentation by Status or Interest in Adopting an Activity-Based Model

Segmentation Variable

abmstatus

		Frequency	Percent	Valid Percent	Cumulative Percent
Derived variable	current/planned ABM	26	27.1	27.1	27.1
	interested	26	27.1	27.1	54.2
	no plan or interest	32	33.3	33.3	87.5
	do not know/no answer	12	12.5	12.5	100.0
	Total	96	100.0	100.0	

Crosstabs by ABM status

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Does your agency currently use a model to study/forecast bicycle or pedestrian trip demand in your region?	Yes, both bicycle and pedestrian trip demand, as separate modes	76.9%	11.5%	9.4%	25.0%
	Yes, bicycle and pedestrian trip demand, grouped as a single "non-motorized" mode	11.5%	19.2%	25.0%	
	Yes, bicycle trip demand, but not pedestrian trip demand	3.8%	3.8%	3.1%	
	No, neither	7.7%	65.4%	62.5%	75.0%
Total		100.0%	100.0%	100.0%	100.0%

For what reasons does you agency use a model (If do not use a model, coded as "no" below)

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Modeling for regional program evaluation	yes	76.9%	34.6%	31.3%	16.7%
	no	23.1%	65.4%	68.8%	83.3%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Modeling for local program evaluation	yes	23.1%	11.5%	21.9%	16.7%
	no	76.9%	88.5%	78.1%	83.3%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Modeling for traffic safety evaluation	yes	3.8%	11.5%	6.3%	8.3%
	no	96.2%	88.5%	93.8%	91.7%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Modeling for active transportation health benefit evaluation	yes	34.6%	11.5%	9.4%	8.3%
	no	65.4%	88.5%	90.6%	91.7%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Modeling for social equity evaluation	yes	30.8%	15.4%	6.3%	8.3%
	no	69.2%	84.6%	93.8%	91.7%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Other reasons	yes	15.4%	7.7%	6.3%	
	no	84.6%	92.3%	93.8%	100.0%
Total		100.0%	100.0%	100.0%	100.0%

Which bicycle modeling approaches do you currently use or are interested in adopting?
(Note: This question is specifically for modeling bicycle trips. A separate question for modeling pedestrian trips this one.)

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Bike trips predicted from an activity-based or tour-based model	Currently use	61.5%			
	Currently developing for future use	15.4%			
	Plan to develop in the next 1-2 years	15.4%			
	Interested in developing, but not currently planned	7.7%	88.5%		
	No plan to develop		11.5%	96.9%	
	Do not know				50.0%
	No answer			3.1%	50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Bike trips predicted from a trip-based model	Currently use	31.8%	23.1%	18.8%	33.3%
	Currently developing for future use	4.5%		6.3%	
	Plan to develop in the next 1-2 years	4.5%			
	Interested in developing, but not currently planned	9.1%	69.2%	25.0%	11.1%
	No plan to develop	50.0%	7.7%	46.9%	
	Do not know			3.1%	55.6%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Bike trips predicted from a bike-specific direct demand model	Currently use	14.3%	3.8%	6.5%	
	Plan to develop in the next 1-2 years	4.8%			
	Interested in developing, but not currently planned	19.0%	53.8%	19.4%	50.0%
	No plan to develop	61.9%	30.8%	71.0%	
	Do not know		11.5%	3.2%	50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Transferring findings from bike route choice models	Currently use	26.1%			
	Plan to develop in the next 1-2 years	8.7%			
	Interested in developing, but not currently planned	26.1%	57.7%	19.4%	33.3%
	No plan to develop	34.8%	26.9%	71.0%	
	Do not know	4.3%	15.4%	9.7%	66.7%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Assigning bicycle trips to a network	Currently use	25.0%	7.7%	9.7%	
	Currently developing for future use	8.3%		3.2%	
	Plan to develop in the next 1-2 years	12.5%	3.8%		
	Interested in developing, but not currently planned	33.3%	73.1%	35.5%	50.0%
	No plan to develop	20.8%	7.7%	51.6%	
	Do not know		7.7%		50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Modeling bike access to transit	Currently use		4.0%	6.3%	
	Currently developing for future use	4.3%		3.1%	
	Plan to develop in the next 1-2 years	4.3%	8.0%		
	Interested in developing, but not currently planned	65.2%	76.0%	43.8%	57.1%
	No plan to develop	17.4%	8.0%	46.9%	
	Do not know	8.7%	4.0%		42.9%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Collection/use of bicycle count data	Currently use	53.8%	38.5%	25.8%	63.6%
	Currently developing for future use	7.7%	7.7%	22.6%	9.1%
	Plan to develop in the next 1-2 years	11.5%	19.2%	6.5%	
	Interested in developing, but not currently planned	15.4%	23.1%	25.8%	9.1%
	No plan to develop	3.8%	7.7%	19.4%	
	Do not know	7.7%	3.8%		18.2%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Collection/use of bicyclist intercept/O-D survey data	Currently use	8.3%	11.5%		25.0%
	Plan to develop in the next 1-2 years	16.7%	11.5%	9.7%	
	Interested in developing, but not currently planned	50.0%	53.8%	35.5%	12.5%
	No plan to develop	8.3%	15.4%	54.8%	12.5%
	Do not know	16.7%	7.7%		50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Collection/use of GPS data specific to bicycle trips	Currently use	16.7%	3.8%	6.5%	22.2%
	Currently developing for future use	4.2%	3.8%	3.2%	11.1%
	Plan to develop in the next 1-2 years	12.5%	11.5%	16.1%	
	Interested in developing, but not currently planned	41.7%	57.7%	41.9%	11.1%
	No plan to develop	12.5%	19.2%	32.3%	11.1%
	Do not know	12.5%	3.8%		44.4%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Use of an all-streets network	Currently use	25.0%	15.4%	9.7%	14.3%
	Currently developing for future use	16.7%	3.8%	6.5%	14.3%
	Plan to develop in the next 1-2 years	8.3%	7.7%	3.2%	
	Interested in developing, but not currently planned	16.7%	46.2%	16.1%	14.3%
	No plan to develop	12.5%	19.2%	48.4%	
	Do not know	20.8%	7.7%	16.1%	57.1%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Use of OpenStreetMap data and/or tools	Currently use	4.2%	15.4%	3.3%	16.7%
	Currently developing for future use	20.8%	3.8%	3.3%	
	Plan to develop in the next 1-2 years	8.3%	3.8%	3.3%	16.7%
	Interested in developing, but not currently planned	20.8%	30.8%	16.7%	
	No plan to develop	25.0%	38.5%	60.0%	16.7%
	Do not know	20.8%	7.7%	13.3%	50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Use of microzone-level detail (e.g. census blocks or parcels) in model	Currently use	8.3%	15.4%	9.7%	25.0%
	Currently developing for future use	29.2%		6.5%	12.5%
	Plan to develop in the next 1-2 years	12.5%	3.8%		
	Interested in developing, but not currently planned	16.7%	46.2%	19.4%	
	No plan to develop	20.8%	26.9%	61.3%	
	Do not know	12.5%	7.7%	3.2%	62.5%
Total		100.0%	100.0%	100.0%	100.0%

Which pedestrian-related data types and collection methods do you currently use or are interested in adopting?

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Walk trips predicted from an activity-based or tour-based model	Currently use	65.4%			
	Currently developing for future use	15.4%			
	Plan to develop in the next 1-2 years	15.4%			
	Interested in developing, but not currently planned		80.8%		
	No plan to develop	3.8%	11.5%	100.0%	
	Do not know		7.7%		50.0%
	No answer				50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Walk trips predicted from a trip-based model	Currently use	36.4%	26.9%	28.1%	33.3%
	Currently developing for future use	4.5%		6.3%	
	Plan to develop in the next 1-2 years			3.1%	
	Interested in developing, but not currently planned	4.5%	50.0%	15.6%	22.2%
	No plan to develop	50.0%	11.5%	43.8%	
	Do not know	4.5%	11.5%	3.1%	44.4%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Walk trips predicted from a mode-specific direct demand model	Currently use	19.0%	11.5%	3.1%	
	Plan to develop in the next 1-2 years		3.8%		
	Interested in developing, but not currently planned	14.3%	50.0%	18.8%	42.9%
	No plan to develop	66.7%	19.2%	78.1%	
	Do not know		15.4%		57.1%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Transferring findings from pedestrian route choice models	Currently use	4.5%			
	Interested in developing, but not currently planned	45.5%	54.2%	12.5%	33.3%
	No plan to develop	45.5%	29.2%	84.4%	
	Do not know	4.5%	16.7%	3.1%	66.7%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Assigning walk trips to a network	Currently use	13.6%	3.8%	6.3%	14.3%
	Plan to develop in the next 1-2 years		7.7%	3.1%	
	Interested in developing, but not currently planned	31.8%	53.8%	25.0%	42.9%
	No plan to develop	54.5%	26.9%	65.6%	
	Do not know		7.7%		42.9%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Detailed modeling of transit walk access and egress trips	Currently use	33.3%	3.8%	15.6%	11.1%
	Currently developing for future use	4.2%		3.1%	
	Plan to develop in the next 1-2 years	4.2%	7.7%		
	Interested in developing, but not currently planned	33.3%	53.8%	37.5%	55.6%
	No plan to develop	20.8%	26.9%	43.8%	
	Do not know	4.2%	7.7%		33.3%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Collection/use of pedestrian count data	Currently use	30.8%	23.1%	25.0%	40.0%
	Currently developing for future use	3.8%	7.7%	9.4%	10.0%
	Plan to develop in the next 1-2 years	11.5%	15.4%	3.1%	
	Interested in developing, but not currently planned	26.9%	42.3%	37.5%	20.0%
	No plan to develop	15.4%	3.8%	25.0%	
	Do not know	11.5%	7.7%		30.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Collection/use of pedestrian intercept/O-D survey data	Currently use	12.0%	7.7%		25.0%
	Currently developing for future use			6.3%	
	Plan to develop in the next 1-2 years	12.0%	3.8%	3.1%	
	Interested in developing, but not currently planned	36.0%	65.4%	31.3%	25.0%
	No plan to develop	28.0%	15.4%	59.4%	
	Do not know	12.0%	7.7%		50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Collection/use of GPS data specific to pedestrian trips	Currently use	8.0%	3.8%	3.1%	12.5%
	Currently developing for future use	20.0%	3.8%		12.5%
	Plan to develop in the next 1-2 years	12.0%	7.7%	6.3%	
	Interested in developing, but not currently planned	28.0%	50.0%	37.5%	25.0%
	No plan to develop	20.0%	26.9%	53.1%	
	Do not know	12.0%	7.7%		50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Use of an all-streets network	Currently use	24.0%	15.4%	15.6%	14.3%
	Currently developing for future use	12.0%	3.8%	6.3%	
	Plan to develop in the next 1-2 years	8.0%	3.8%		14.3%
	Interested in developing, but not currently planned	16.0%	42.3%	15.6%	28.6%
	No plan to develop	24.0%	23.1%	53.1%	
	Do not know	16.0%	11.5%	9.4%	42.9%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Use of OpenStreetMap data and/or tools	Currently use		7.7%	3.2%	
	Currently developing for future use	16.0%	3.8%	3.2%	
	Plan to develop in the next 1-2 years	16.0%		3.2%	
	Interested in developing, but not currently planned	16.0%	38.5%	19.4%	50.0%
	No plan to develop	32.0%	42.3%	58.1%	
	Do not know	20.0%	7.7%	12.9%	50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Use of microzone-level detail (e.g. census blocks or parcels) in model	Currently use	12.0%	11.5%	15.6%	14.3%
	Currently developing for future use	20.0%		3.1%	
	Plan to develop in the next 1-2 years	12.0%			14.3%
	Interested in developing, but not currently planned	20.0%	46.2%	18.8%	28.6%
	No plan to develop	24.0%	30.8%	62.5%	
	Do not know	12.0%	11.5%		42.9%
Total		100.0%	100.0%	100.0%	100.0%

		current/planned ABM	interested	no plan or interest	do not know/no answer
Are there any bicycle or pedestrian modeling approaches or data types your agency is using that were not listed in the preceding questions?	No	88.0%	96.2%	96.9%	80.0%
	Yes, bicycle-related	4.0%			
	Yes, pedestrian-related	4.0%			10.0%
	Yes, bicycle- and pedestrian-related	4.0%	3.8%	3.1%	10.0%
Total		100.0%	100.0%	100.0%	100.0%

How important are the following issues as impediments to your agency's development of tools or approaches for modeling bicycle and/or pedestrian demand?

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Availability of staff time	Very important	73.1%	61.5%	50.0%	70.0%
	Somewhat important	23.1%	30.8%	37.5%	30.0%
	Not very important		3.8%	9.4%	
	Not important at all	3.8%		3.1%	
	Not applicable/do not know		3.8%		
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Level of staff training	Very important	42.3%	53.8%	18.8%	50.0%
	Somewhat important	23.1%	23.1%	50.0%	20.0%
	Not very important	26.9%	15.4%	25.0%	30.0%
	Not important at all	7.7%		6.3%	
	Not applicable/do not know		7.7%		
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Funding for staff and/or consultant time	Very important	61.5%	50.0%	50.0%	60.0%
	Somewhat important	26.9%	30.8%	37.5%	10.0%
	Not very important	7.7%	15.4%	9.4%	30.0%
	Not important at all	3.8%		3.1%	
	Not applicable/do not know		3.8%		
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Funding for computing resources	Very important	15.4%	30.8%	21.9%	54.5%
	Somewhat important	34.6%	26.9%	21.9%	9.1%
	Not very important	38.5%	26.9%	43.8%	36.4%
	Not important at all	11.5%	7.7%	9.4%	
	Not applicable/do not know		7.7%	3.1%	
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Funding for data collection and/or acquisition	Very important	53.8%	65.4%	46.9%	45.5%
	Somewhat important	46.2%	26.9%	37.5%	45.5%
	Not very important		3.8%	12.5%	9.1%
	Not important at all			3.1%	
	Not applicable/do not know		3.8%		
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Lack of agency consensus on modeling/research priorities	Very important	15.4%	15.4%	15.6%	20.0%
	Somewhat important	26.9%	19.2%	31.3%	10.0%
	Not very important	34.6%	50.0%	40.6%	20.0%
	Not important at all	23.1%	3.8%	9.4%	30.0%
	Not applicable/do not know		11.5%	3.1%	20.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Lack of clear guidance from the modeling/research community	Very important	11.5%	23.1%	18.8%	36.4%
	Somewhat important	42.3%	50.0%	25.0%	18.2%
	Not very important	26.9%	11.5%	34.4%	9.1%
	Not important at all	15.4%	3.8%	15.6%	18.2%
	Not applicable/do not know	3.8%	11.5%	6.3%	18.2%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Lack of training courses or seminars directly related to modeling bike/pedestrian demand	Very important	15.4%	26.9%	15.6%	36.4%
	Somewhat important	30.8%	46.2%	40.6%	18.2%
	Not very important	38.5%	11.5%	31.3%	9.1%
	Not important at all	11.5%	3.8%	6.3%	18.2%
	Not applicable/do not know	3.8%	11.5%	6.3%	18.2%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Are there any impediments that your agency faces in modeling bicycle and/or pedestrian travel demand that were not listed in the previous questions?	Yes (Please provide a brief description)	15.4%	28.0%	12.5%	27.3%
	No	84.6%	72.0%	87.5%	72.7%
Total		100.0%	100.0%	100.0%	100.0%

Classification questions as column percentages

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
Is your agency a regional MPO or state DOT?	Regional MPO	76.9%	84.6%	62.5%	83.3%
	State DOT	23.1%	15.4%	37.5%	16.7%
Total		100.0%	100.0%	100.0%	100.0%

Classification questions for State DOT respondents

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
How many travel modeling staff does your agency have?	0-2	33.3%	25.0%	50.0%	
	3-4	33.3%	25.0%	16.7%	
	5-9	16.7%	50.0%	33.3%	100.0%
	10 or more	16.7%			
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
What is the population of your state?	Less than 1.5 million			8.3%	
	1.5 million to 3.5 million	16.7%	25.0%	41.7%	
	3.5 million to 5.5 million	33.3%			
	5.5 million to 8 million	16.7%	25.0%	8.3%	
	Over 8 million	33.3%	50.0%	41.7%	100.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
What is your state's bike mode share for commute trips?	0-0.5%	40.0%	25.0%	50.0%	50.0%
	0.5-1%			33.3%	
	1% or greater	20.0%	25.0%		
	Don't know	40.0%	50.0%	16.7%	50.0%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
What is your state's walk mode share for commute trips?	0-1%	60.0%	25.0%	41.7%	
	1-3%			25.0%	50.0%
	3% or greater		25.0%	16.7%	
	Don't know	40.0%	50.0%	16.7%	50.0%
Total		100.0%	100.0%	100.0%	100.0%

Classification questions for Regional MPO respondents

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
How many travel modeling staff does your agency have?	None		31.8%	10.5%	30.0%
	1-2	25.0%	45.5%	89.5%	70.0%
	3-4	30.0%	18.2%		
	5 or more	45.0%	4.5%		
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
What is the population of your region?	Less than 250,000	10.0%	27.3%	42.1%	55.6%
	250,000 to 500,000	5.0%	27.3%	26.3%	11.1%
	500,000 to 1 million	10.0%	22.7%	21.1%	22.2%
	1 million to 2.5 million	25.0%	9.1%	5.3%	
	2.5 million to 5 million	25.0%	9.1%		11.1%
	Over 5 million	25.0%	4.5%	5.3%	
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
What is your region's bike mode share for commute trips?	0-1%	35.0%	59.1%	47.4%	33.3%
	1-3%	50.0%	9.1%	36.8%	22.2%
	3% or greater	15.0%		10.5%	22.2%
	Don't know		31.8%	5.3%	22.2%
Total		100.0%	100.0%	100.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer
What is your region's walk mode share for commute trips?	0-1%	15.0%	27.3%	5.3%	11.1%
	1-4%	55.0%	40.9%	63.2%	44.4%
	4% or greater	30.0%		21.1%	22.2%
	Don't know		31.8%	10.5%	22.2%
Total		100.0%	100.0%	100.0%	100.0%

Classification questions as row percentages

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
Is your agency a regional MPO or state DOT?	Regional MPO	27.8%	30.6%	27.8%	13.9%	100.0%
	State DOT	25.0%	16.7%	50.0%	8.3%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
How many travel modeling staff does your agency have?	0-2	22.2%	11.1%	66.7%		100.0%
	3-4	40.0%	20.0%	40.0%		100.0%
	5-9	11.1%	22.2%	44.4%	22.2%	100.0%
	10 or more	100.0%				100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
What is the population of your state?	Less than 1.5 million			100.0%		100.0%
	1.5 million to 3.5 million	14.3%	14.3%	71.4%		100.0%
	3.5 million to 5.5 million	100.0%				100.0%
	5.5 million to 8 million	33.3%	33.3%	33.3%		100.0%
	Over 8 million	18.2%	18.2%	45.5%	18.2%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
What is your state's bike mode share for commute trips?	0-0.5%	20.0%	10.0%	60.0%	10.0%	100.0%
	0.5-1%			100.0%		100.0%
	1% or greater	50.0%	50.0%			100.0%
	Don't know	28.6%	28.6%	28.6%	14.3%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
What is your state's walk mode share for commute trips?	0-1%	33.3%	11.1%	55.6%		100.0%
	1-3%			75.0%	25.0%	100.0%
	3% or greater		33.3%	66.7%		100.0%
	Don't know	28.6%	28.6%	28.6%	14.3%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
How many travel modeling staff does your agency have?	None		58.3%	16.7%	25.0%	100.0%
	1-2	12.8%	25.6%	43.6%	17.9%	100.0%
	3-4	60.0%	40.0%			100.0%
	5 or more	90.0%	10.0%			100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
What is the population of your region?	Less than 250,000	9.5%	28.6%	38.1%	23.8%	100.0%
	250,000 to 500,000	7.7%	46.2%	38.5%	7.7%	100.0%
	500,000 to 1 million	15.4%	38.5%	30.8%	15.4%	100.0%
	1 million to 2.5 million	62.5%	25.0%	12.5%		100.0%
	2.5 million to 5 million	62.5%	25.0%		12.5%	100.0%
	Over 5 million	71.4%	14.3%	14.3%		100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
What is your region's bike mode share for commute trips?	0-1%	21.9%	40.6%	28.1%	9.4%	100.0%
	1-3%	47.6%	9.5%	33.3%	9.5%	100.0%
	3% or greater	42.9%		28.6%	28.6%	100.0%
	Don't know		70.0%	10.0%	20.0%	100.0%

		current/ planned ABM	interested in ABM	no plan or interest for ABM	do not know/ no answer	Total
What is your region's walk mode share for commute trips?	0-1%	27.3%	54.5%	9.1%	9.1%	100.0%
	1-4%	30.6%	25.0%	33.3%	11.1%	100.0%
	4% or greater	50.0%		33.3%	16.7%	100.0%
	Don't know		63.6%	18.2%	18.2%	100.0%