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ESTIMATION AND SIMULATION OF DAILY ACTIVITY PATTERNS FOR INDIVIDUALS USING WHEELCHAIRS

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4501 South 2700 West - P.O. Box 148410 - SLC,UT 84114-8410

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16. Abstract
Individuals who use wheelchairs or who have other mobility challenges often are unable to access modern mobility systems – including application-based ride hailing and on-demand microtransit. Even designing a system targeted at these users is challenging, given the limited prior analysis of their travel behavior and activity patterns. Simulation tools are used by cities around the world to understand novel and complex transportation systems, yet few are including the needs of users with disabilities in these simulation studies. This report examines the travel patterns of wheelchair users from the 2017 National Household Travel Survey, and presents a model of daily activity pattern choice of respondents who self-identify as using a wheelchair. This report discusses the application of a wheelchair status variable in the activity-based travel demand model ActivitySim and measures its effect on individual and household daily activity pattern choice. Wheelchair use is estimated to reduce the utility of a work daily activity pattern by 1.9 points relative to a home pattern for full-time workers and 3.4 for part-time workers. Including the effect of wheelchair use in a regional daily activity pattern model resulted in 21.9 percent of wheelchair users changing to a home activity pattern relative to a base scenario not including wheelchair use. Lastly, the report evaluates the performance of an on-demand, accessible mode for users with wheelchairs in the agent-based microsimulation BEAM. This simulation showed that demand for such a service increases linearly with fleet size and wait time remains constant, though further scenario refinement and research is necessary.

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LIST OF ACRONYMS

ACS	American Community Survey
ADA	Americans with Disabilities Act
AGRC	Automated Geographic Reference Center
AV	Autonomous Vehicle
BTS	Bureau of Transportation Statistics
CDAP	Coordinated Daily Activity Pattern
DAP	Daily Activity Pattern
DRT	Demand Rapid Transit
FHWA	Federal Highway Administration
GTFS	General Transit Feed Specification
MAG	Mountainland Association of Governments
MSA	Metropolitan Statistical Area
MTC	Metropolitan Transportation Commission
NHIS	National Health Interview Survey
NHTS	National Household Travel Survey
PUMS	Public Use Micro-Sample
RFP	Request for Proposal
TAZ	Traffic Analysis Zone
TNC	Transportation Network Company
UDOT	Utah Department of Transportation
UTA	Utah Transit Authority
WAV	Wheelchair-accessible vehicle
WFRC	Wasatch Front Regional Council

EXECUTIVE SUMMARY

As the transportation system in Utah becomes more diverse with new modes such as on-demand taxis, car sharing, bikes / scooters, and potential autonomous vehicles, there is a growing need to understand mobility patterns of individuals with travel-limiting disabilities, including the use of a wheelchair. Previous research has shown that disabilities have a negative effect on travel behavior in a variety of contexts (trip length, mode, etc.), but in considering the use of a wheelchair, no study has quantified the effect of wheelchair use in the context of a travel model. This report contains two primary contributions to the research surrounding mobility for individuals using wheelchairs. The first is an understanding of the effect of wheelchair use on one's choice of daily activity pattern. These patterns were evaluated using both a calibrated activity-based model of Salt Lake City and a rigorous study of choice behavior using data from the 2017 NHTS. The second contribution was an application of this understanding in modeling a simulation of wheelchair-accessible vehicles.

The study shows that use of a wheelchair places significant constraints on an individual's daily activity pattern choice behavior. Consequently, we recommend that UDOT apply this understanding to planning models in the state to better understand the equity implications of its projects. This report also provides a foundation to further research on the effect of wheelchair use in considering other travel activity models such as mode choice or trip length; in this way the study methodology provides an illustration of more behaviorally sensitive travel models were UDOT or its partners to consider adopting such models for their planning activities The simulation results presented in this report do not show a diminishing marginal benefit for additional wheelchair-accessible vehicles; this could imply a large currently unmet demand for such a service that should be investigated.

CHAPTER 1 INTRODUCTION

1.1 Problem Statement

In December 2018, the Utah Transit Authority (UTA) released a request for proposals (RFP) to offer on-demand transportation services for wheelchair-using passengers in Salt Lake County (UTA, 2018). The RFP described a 6-month pilot study, wherein individuals with wheelchairs would be able to request on-demand transportation services from a major transportation network company (TNC). The TNC would serve the requests using a fleet of wheelchair-accessible vehicles (WAV) provided under agreement with UTA and drivers whom UTA would train to operate the special equipment and interface with wheelchair-using passengers.

In developing this RFP, UTA encountered a great deal of uncertainty related to the design and operation of this system. How many people will use it? How many vehicles would be necessary to offer a minimal level of service? What should be the geographic boundaries of this service? No existing tool could provide any coherent attempt at answering these questions.

In January 2019, UTA partnered with Lyft to deploy the WAVs. However, after months of negotiation and due to complications with data sharing and concerns with liability, the pilot was never launched. This does not mean that the questions are invalid, and transit agencies continue to explore possibilities for improved mobility for users with wheelchairs and seek more clarity related to the design and operation of such systems.

1.2 Objectives

This research, as inspired by the questions and uncertainty surrounding the UTA WAV pilot project, includes two primary objectives and contributions. The first objective is to understand the effect that an individual's wheelchair use has on their choice of daily activity pattern (DAP), all else equal; the second objective is to use this understanding to model a WAV system and evaluate its performance. These objectives, along with the steps taken necessary to reach the contributions mentioned, are outlined in Figure 1-1. The individual pieces of Figure 1-1 are explained in the outline in Section 1.3.

Two central pieces of software were used to accomplish the objectives of the research. ActivitySim (ActivitySim, 2021) generates DAP for a synthetic population based on calibrated choice models and travel-time measurements. BEAM (Behavior, Energy, Autonomy, Mobility; Bae et al., 2019) simulates a population, also called agents, accomplishing their DAP given a description of a region's transportation services; BEAM also allows agents to adapt their DAP to best utilize new transportation services. Both ActivitySim and BEAM are open-source software platforms with wide and growing user bases; details of these software and their specific inputs will be discussed in the report as appropriate.

1.3 Outline of Report

Chapter 1 introduces and outlines the objectives and organization of the report, followed by a Literature Review in Chapter 2 discussing first, the literature and existing research surrounding the travel behavior of individuals with disabilities and second, existing simulations of ride-hail scenarios using multiagent simulation tools. Chapter 2 presents the need for further understanding of travel behavior patterns of individuals with wheelchairs and that this specific population has not been effectively modeled in traditional simulation research, especially with regard to WAVs.

Chapter 3 introduces ActivitySim, the activity-based model chosen to generate DAP for the Greater Salt Lake Area by describing its input setup, validation, and calibration. Chapter 3 introduces the synthetic population, a data set containing persons and attributes that represent the Salt Lake Area, and a set of travel model network skims; these network skims inform the model on travel times and cost. This chapter also describes the validation and calibration of ActivitySim to the Salt Lake Area, using target values from the Wasatch Front Regional Council / Mountainland Association of Governments (WFRC / MAG) travel demand model. The primary components of this chapter are represented in green in Figure 1-1.

Chapter 4 contains the first primary contribution of the research: an understanding of the effect that wheelchair use has on the choice of DAP; this process is represented by the red elements in Figure 1-1, and the contribution is represented in grey. To estimate this effect, we first identified wheelchair users from the 2017 National Household Travel Survey (NHTS;

FHWA, 2017), and estimated their DAP choice behavior using multinomial logit models. With these estimated choice coefficients, we simulate their behavior in the calibrated ActivitySim scenario and compare the results to their behavior from a base scenario. The findings show that wheelchair users are more likely to choose a home DAP – all else equal – and will be explained in further detail in Chapter 4.

Chapter 5 is represented by the blue in Figure 1-1 and includes the second primary contribution of this research: a measure of the performance of a WAV system, using the understanding from Chapter 4. Chapter 5 describes the setup and use of the microsimulation tool BEAM and shows how scenarios were built to compare the operation and utilization of WAVs in an on-demand ride-hailing network.

Finally, Chapter 6 concludes the report by restating the contributions of this research, explaining the limitations, and proposing next steps for future research.

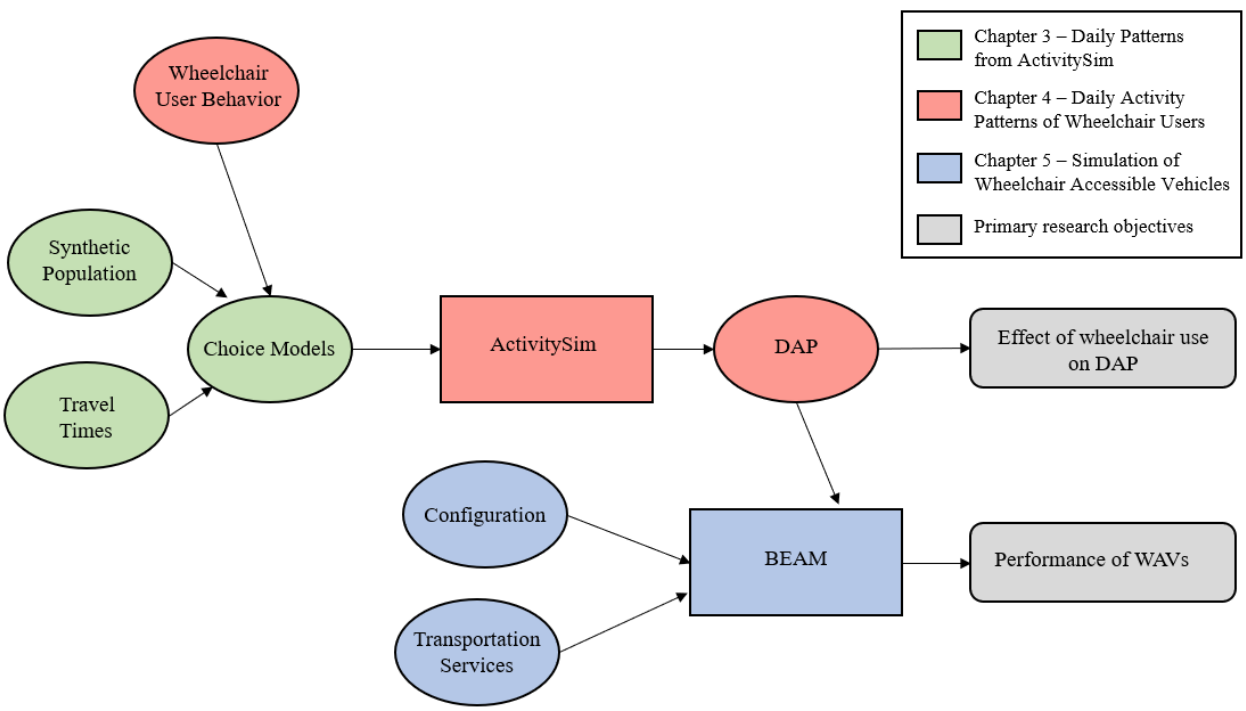

Figure 1-1 Overview of research and organization of report.

CHAPTER 2 LITERATURE REVIEW

2.1 Overview

The objectives of this research are two-fold: First, the research aims to understand the effect of wheelchair use on choice of DAP; the second objective is to use this understanding of behavior to model a WAV system. These objectives necessitate a review of two different sets of literature that have not to this point intersected in meaningful ways. The first literature set observes how the daily travel and activity patterns of wheelchair users and other individuals with ambulatory limitations differ from the patterns of the population typically considered by travel demand forecasting models. The second literature set considers attempts to forecast the adoption and use of on-demand mobility services in any population segment. This chapter presents a review of academic and professional works on each of these topics in succeeding sections. The chapter ends with a consideration of existing mobility services for users with disabilities, and a discussion of recent regulatory and legislative actions relevant to these mobility services.

2.2 Mobility Patterns of Users with Disabilities

According to data in the NHTS (FHWA, 2017), the share of people in the United States with travel-limiting disabilities increased from 8.5 percent of the population in 2001 to 10.2 percent in 2009 (Brumbaugh, 2018). In the 2017 NHTS, this share returned to 8.5 percent by our own calculations. As of 2018, an estimated 13.4 million Americans age 18 to 64 have travel-limiting disabilities, accounting for slightly more than half of people with any disabilities (Brumbaugh, 2018). Given that difficulties in travel appear to result in decreased employment opportunities (Rosenbloom, 2007) and may negatively influence general quality of life, understanding the effects of limitations on travel is an important policy and planning objective.

Mobility for users with disabilities as a general topic has been studied in regards to accessible transportation (Curl et al., 2011; Darcy & Burke, 2018; Jonnalagedda et al., 2014), mobility for the elderly (Ball et al., 1998; Li & Tilahun, 2017; Rosenbloom, 2001), tourism travel and disabilities (Burnett & Baker, 2001; Darcy, 2010), and Dial-a-Ride service optimization (Fu, 2002; Kurauchi et al., 2007). While these topics provide valuable background on the general transportation of individuals with disabilities, the focus of our analysis is primarily the daily activity and travel patterns of users with disabilities such as the purpose and frequency of trips and the modes used. Rosenbloom (2007) provides an overview on the subject of transportation patterns and problems of people with disabilities in Appendix G of the book *The Future of Disability in America.* This literature review covers information and research on overall travel patterns including mode, frequency, and purpose. It also included topics such as driving for the aging community (ECMT, 1999; Gagliardi et al., 2005; Hu & Reuscher, 2004; OECD, 2001; Rosenbloom & Stähl, 2003), public agencies and their compliance to the Americans with Disabilities Act (ADA), paratransit and buses (Thole & Harvey, 2005), and the pedestrian environment (Kihl et al., 2005; Kocera et al., 2005). The literature of this research project will describe findings related to the purpose and frequency of trips and the mode choice of trips.

2.2.1 Trip Purpose and Tour Frequency

Disability can have a major effect on the frequency of trips made by an individual. Sweeney (2004) compared groups by number of times individuals left the house per week and by private motor vehicle usage. They found that the elderly with disabilities leave their home less often than both of the younger age groups (4.0 days per week for 65+, 5.1 days per week for 25-64, and 5.6 days per week for <25). The study shows that people with disabilities traveled less and also reported more mobility problems than those without disabilities. There were individuals that were unable or unwilling to leave their houses because their disabilities were so severe. According to Sweeney, almost 2 million individuals with disabilities were homebound—this includes 9.0 percent of those ages 65 and over. In the same study, two-thirds of individuals with disabilities under 65 left their homes daily.

Another study (Beyene et al., 2009) shows that driving status does not affect the mobility out of the home for users with disabilities. In a survey of 80 subjects in New Delhi, India, the authors present community mobility trends by driving status among people with disabilities and senior citizens. Their findings show that driving status does not impact mobility out of the home. They also found that individuals with a higher level of education may be associated with higher frequency of leaving the home. Some of these findings may be context-dependent and may not apply to the North American situation.

The disability of an individual can affect one's trip purpose. Schmöcker et al. (2005) estimated trip generation using data from the 2001 London Area Travel Survey. The authors found that as individuals become older and disabilities interfere, trip-making decreases. Schmöcker et al. also saw that among groups of young disabled, younger elderly, and older elderly people, retired individuals initially made the most trips. Ermagun et al. (2016) also elaborates on patterns of trip purpose of disabled persons along with the way they are accompanied to those activities. In this study, they developed models to measure the dependency of individuals with disabilities on others for transportation. They found that when making a healthcare trip, those with disabilities were more dependent on an escort.

Healthcare activities are a common destination for users with disabilities and they often affect the mode and frequency of travel for individuals. Sweeney (2004) shows that auto use for example, often as the driver, was even higher for medical trips among all travelers with disabilities than for the general population. This study found that among those with disabilities ages 25 to 64, almost 9 out of 10 travelers reported using a personal vehicle to travel to the doctor, whether as the driver or the passenger. Less than 2.0 percent reported using ADA or other specialized paratransit to travel to a doctor, and less than 4.0 percent took a public bus.

2.2.2 Mode Choice

Americans with disabilities have been shown to rely heavily on private vehicles as drivers or passengers (Rosenbloom, 2001; Sweeney, 2004). Sweeney (2004) examined the travel patterns of older Americans with disabilities and compared these patterns to older Americans without disabilities and younger Americans with disabilities. She compared local travel to long-distance travel and also compared mode choice distribution. Sweeney used the responses from the Bureau of Transportation Statistics' *Transportation Availability and Use Survey* (USDOT, 2003), where 5,019 interviews were completed, and 2,321 respondents had disabilities (survey weights were developed to reduce bias). The severity of each disability varies and even more so as age increases. The results show that the elderly, both abled and disabled, rely on the private vehicle as a primary mode for both local and long-distance travel. Those with disabilities tend to ride as passengers instead of as drivers, and a small percentage of the elderly disabled used alternate modes (4.0 percent took a bus and 2.0 percent took paratransit) while about one-third walked. Rosenbloom (2007) writes that nondrivers with disabilities were remarkably reliant on the car—and even more so if taxi use is included. Over 86.0 percent of nondrivers were passengers in a car, 16.0 percent rode in a type of carpool, and almost 22.0 percent used a regular taxi during the previous month.

Nearly 15 years later, Bascom & Christensen (2017) compare findings from the 2003 Bureau of Transportation Statistics (BTS) national survey with their own survey of 193 respondents on private vehicle usage. They reported that 32.9 percent of individuals with disabilities utilize a private vehicle, which is considerably less than the national rate reported by the BTS national survey at 61.0 percent. They also show that of the 76.6 percent of respondents with a licensed driver in the household, 85.3 percent had not driven a vehicle within the past month primarily due to their disability. The Bascom & Christensen study was not a study of observed behavior, but rather a stated-preference survey of how the subjects would most likely behave. For drivers, Rosenbloom (2007) found that persons with disabilities were more likely to limit their driving in unideal scenarios such as bad weather, busy roads/intersections, nighttime, and peak hours, and they would avoid driving long distances and on unfamiliar roads. Her review also shows that while the car is primarily used, its use is not correlated with severity of the disability, and that some individuals have disabilities so severe that they cannot walk, yet they can drive. Others have disabilities that even limit their mobility within the home, in which case transportation is only a secondary issue.

Individuals with physical disabilities have reported difficulties using many transportation systems (Bascom & Christensen, 2017). Often modes of transport are difficult to access or unavailable altogether. According to the Rosenbloom (2007) review of a 1994 supplement to the National Health Interview Survey (NHIS), roughly a third of the respondents reported that there was no public transportation available in their area. Even among the majority who reported to have transit, most did not use it—and health/disability was not the reason for non-use. Rosenbloom reports that more than three-fourths who had transit in the area did not use it during the last 12 months and less than 10.0 percent reported using bus or subway in the last week. Where there were specialty services such as paratransit available, only 10.0 percent reported using the service at all during the last 12 months. Respondents reported to be twice as likely to pay full price for a regular taxi, according to Rosenbloom (2007). Brumbaugh (2018) reported that less than 3.0 percent of people with disabilities use paratransit, while 4.6 percent of people with disabilities report using ride-hailing services at least once in the last 30 days. In contrast and from the NHIS analyzed by Rosenbloom (2007) nearly 10 years earlier, less than 13.0 percent of nondrivers used ADA paratransit services and under 7.0 percent used other community paratransit services in that month. Bascom & Christensen (2017) reported results showing that the number of participants who used public transportation was triple that reported in the previous NHIS study (Rosenbloom, 2007), and the number of respondents who indicated they made use of paratransit as well as those who indicated riding with others were both greater than what was represented in the NHIS study. Note that these contradictions may be due to groups sampled in each study. People with disabilities are more reliant on for-hire services, in particular taxicabs, than non-disabled persons. While non-disabled people make, on average, 4.1 for-hire trips annually, people with disabilities make twice as many trips (Schaller, 2018). According to this study, people with disabilities are also more reliant on taxicabs than the general population. It also shows that people with disabilities take 5.9 taxi trips annually, twice their use of TNCs (2.3 trips per year).

Mode choice for users with disabilities can be influenced by a number of factors. Bascom & Christensen (2017) reported that participants' social networks effect their transportation mode choices, and that socializing with family was correlated with transportation mode choices in that family helps meet transportation needs for socializing. They also found that income level and disability type also affect an individual's transportation mode choices, and that individuals with physical disabilities relied on public transportation more than those with other disability types. Of individuals who used public transportation, those with disabilities most often earned significantly lower incomes than those who were able to drive personal vehicles, by about $10,000 annually (Bascom & Christensen, 2017). In a poll summarized by Rosenbloom (2007), they "found that almost two-thirds of all the people with disabilities who reported major transportation problems had annual incomes below $35,000" (p. 521). For those with higher incomes, there were fewer transportation problems.

2.2.3 Mobility Patterns for Users with Wheelchairs

Users with wheelchairs face additional challenges in transportation compared with the general population of individuals with disabilities. Velho et al. (2016) found that users with wheelchairs face two categories of barriers, physical and attitudinal. Wheelchair users who use public transport in London discuss a variety of physical barriers encountered while traveling, such as the layout of the interior of the bus and broken elevators. All 27 wheelchair-using interviewees in the Velho et al. study discussed barriers of this nature, with no exceptions. Responses range from malfunction of ramps and elevators to sounds of caution (when deploying ramps) as sounds of shame.

In a study on accessibility for disabled individuals, Van Roosmalen et al. (2010), showed that solutions have been improving over the years. They found that wheelchair lifts have been used for more than 30 years and have drastically changed the mobility of individuals who have disabilities, allowing wheelchair users to be independent and mobile. Their findings show that mobility, including the ability to get out and about, interact with the community, and be employed are impactful on a person's well-being.

It is important to note a wide variance in the results; this variance could come from a range of factors including modal availability by geographic region, difference in years from ADA, vehicle availability, or possession of a driver's license in the household. While some studies account for some or all of these variables, severity of disability is not quantified in any of these studies. While severity is considered by some of the mentioned researchers, it could be a factor in the variance of conclusions observed in this review of the literature. This is just an example that supports the observation that without a regularized attempt to observe the travel behavior of individuals with disabilities, ad-hoc studies on widely divergent populations will result in a variety of conclusions.

2.3 Forecasting On-Demand Services

While the research of this project is focused on understanding the travel behavior of individuals with wheelchairs, it also aims to lay a framework to model and simulate their behavior in an on-demand ride-hail scenario. The literature mentioned to this point is helpful to the research of this project, as it acts as a starting point and direction to eventually develop estimation models to simulate persons with disabilities. Now considering research regarding these simulations of general populations in micromobility scenarios, many studies have simulated on-demand transportation services. Simulation tools have been used to evaluate the performance of transportation systems from as early as 1970 (Wilson et al., 1970). This section will focus on the work of researchers using simulation tools to evaluate the performance of on-demand transportation systems.

Agatz et al. (2011) built a trip-based simulation model to match drivers and riders in an on-demand taxi setting. The research aimed to minimize total vehicle miles traveled and individual travel costs from travel demand data in Atlanta, GA. Their methods solved dynamic ride-share matching problems using computer simulations in C++ and was based on actual travel demand data. The research demonstrated the value of optimization techniques over “greedy matching methods” and suggested that future simulations should consider carpooling and occupancy dependent travel times. Cheng & Nguyen (2011) developed a multi-agent-based simulation platform Taxisim to adequately model realistic taxi fleet operations. They incorporated their analysis on the real-world behavior of self-interested taxi drivers by designing a background agent movement strategy.

Vosooghi et al. (2017) published a literature review on the subject of travel demand estimation for carsharing systems. In this review, they concluded that activity-based models are more effective than trip-based models at demand forecasting and at modeling new and advancing modes such as one-way car sharing. The authors also noted that ride-sharing in a carsharing network, which had not yet been considered, is a likely part of an innovative carsharing system. They showed how researchers have used a random utility model (Catalano et al., 2008) and a discrete choice model (Kouwevhoven et al., 2011) to predict demand of a one-way carsharing service. They also highlighted three major simulation tools, SimMobility (Azevedo et al., 2016), MobiTopp (Heilig et al., 2015), and MATSim (Multi-Agent Transportation Simulation; Balac et al., 2015; Ciari et al., 2014; Fagnant & Kockelman, 2014; Horl et al., 2016), comparing the work performed over the years.

Using the activity-based SimMobility, Azevedo et al. (2016) modeled the supply and demand of an autonomous taxi network in a car-restricted zone of Singapore. Their research proposed an extension to SimMobility at the short-term and midterm levels to simulate automated vehicle (AV) taxi systems and their effects on travel behavior. They tested different fleet sizes and parking station configurations to observe changes in modal shares, routes, and destinations.

Another mode that presents challenges and opportunities for researchers to study using simulations is demand rapid transit (DRT). This mode is also known as dial-a-ride, paratransit or flexible-route service, and literature on this subject can be found from the 1960s onwards, as summarized by Parragh et al. (2010). In a literature review published by Ronald et al. (2015) on the subject of simulating DRT, the authors concluded that agent-based simulations permit consideration of the user's performance rather than the operators' optimization. According to their review, agent-based simulations have been used for shared taxis (Ciari et al., 2009; Martinez et al., 2013), ride-sharing (Kleiner et al., 2011) and carpooling (Dubernet et al., 2013).

Fu (2002) attempted to simulate the operations of a dial-a-ride paratransit. Using the simulation platform SimParatransit, written in C++, he evaluated the operational performance of the system to test if automatic vehicle location technology would improve the schedules of the vehicles. Years later, Quadrifoglio et al. (2008) explored the impact of time windows for DRT service in Los Angeles County in their simulation. In a more recent study, Oh et al. (2020) used agent-based simulations to extend SimMobility to model an on-demand, shared, and automated minibus service.

While simulation is widely used to model on-demand transport services, not all analyses use simulation. For example, Lin et al. (2018) showed how a bike share placement problem can be solved using a neural network. Basciftci & Van Hentenryck (2019) proposed a bilevel optimization approach to observe the mode choice of individuals in Ann Arbor, Michigan. Zhao et al. (2018) used machine learning and logit models to model on-demand transit and mode choice. Turmo et al. (2018) used mathematical models to predict which users switch from paratransit to taxi service if a combined program were implemented. Alonso-Mora et al. (2017) used mathematical models for high-capacity ride-sharing that scale to large numbers of passengers and optimize routes with respect to demand locations. Ke et al. (2017) proposed a deep learning approach to model passenger demand in an on-demand ride service platform.

One tool worth mentioning, called MATSim (Horni et al., 2016), is a Java-based transportation microsimulation developed since 2006 by a team within the Institute for Land and Maritime Transportation at the Technical University of Berlin. MATSim combines a detailed link-level transportation simulation with an evolutionary algorithm to adjust individual daily plans and identify system optima. The agents in MATSim attempt to execute activity plans that require them to travel between their activities along transportation networks that become congested as people use them. At the end of a transportation simulation, each agent considers how much time they spent doing activities (generating a benefit) and how much time they spent traveling (losing benefits). Each agent will then adjust their plans — change departure time, use a different travel mode, take a different route, etc. — and after several dozen iterations, each simulated agent will have a complete daily plan that maximizes their personal benefit weighted against fares, incomes, vehicle constraints, the congestion created by the choices of others, etc. The combination of a detailed simulation with a simple but powerful plan updater has made MATSim appealing to many researchers seeking to understand complex modern mobility systems.

Extensions to MATSim led researchers to examine carsharing in Zürich (Balać et al., 2015), autonomous vehicle replacement scenarios in Berlin (Bischoff & Maciejewski, 2016) and Asheville, North Carolina (Kressner et al., 2016), demand-responsive and autonomous transit in Brunswick, Germany (Cyganski et al., 2018), incident and disaster response in the Philippines (Yaneza, 2016), and first-mile / last-mile connectivity in the San Francisco Bay area of California (Jaller & Rodier, 2019). Viergutz & Schmidt (2019) also used MATSim to compare conventional public transportation to DRT in a rural town in Germany.

In a study relevant to the simulation of individuals with wheelchairs, Bischoff (2019) simulated WAVs as a chapter of a dissertation of on-demand taxis in Berlin, using MATSim. To create daily activity patterns, he noted that “transport patterns of persons with mobility impairments have not been evaluated” (p. 74), and to estimate demand, he assumed that the current paratransit systems would be completely replaced. From statistics for the subsidized paratransit and taxi service in 2015, he estimated there are about 1,000 trips per day and that the trips are similar to non-work trips (neither the paratransit nor the taxi are used for work commutes). Using the existing MATSim scenario for the city of Berlin (Ziemke et al., 2015), 10 random samples of 1,000 non-work trips were marked with a “wheelchair-friendly” requirement. The number of wheelchair-accessible taxis varied from 50 to 500 of the existing taxi supply in Berlin. Bischoff found that with 250 WAV vehicles (well below 5.0 percent of the city’s active vehicle fleet) an estimated wait time of 12:22 minutes is achieved (the target wait time was 15 min). The taxi dispatching algorithm assigned the nearest vehicle to a customer, which means that WAVs will not exclusively serve wheelchair users. One consequence of this algorithm is that the number of required WAVs increases, however, this behavior is realistic and optimizes the revenue of the drivers.

As a part of Bischoff’s (2019) study, the users limited to a wheelchair were marked as a separate population and the WAVs served both the wheelchair-limited and the abled populations; however, the methodology for estimating demand was rudimentary in that “the possible number of such trips is hard to estimate” (p. 74) and “there is no information about origins and destinations of these trips, either” (p. 75). Trips were estimated by averaging rides from paratransit and taxi rides in Berlin; this number is nearly doubled without explanation to pattern weekday behavior. This provides an opportunity to more accurately estimate travel patterns of individuals with wheelchairs and simulate their behavior.

Built on the modeling framework of MATSim, BEAM (Bae et al., 2019) utilizes more specific ride-hailing integration. BEAM stands for Behavior, Energy, Autonomy, and Mobility and is an agent-based microsimulation model developed at Lawrence Berkeley National Laboratory and the UC Berkeley Institute for Transportation Studies. BEAM was developed to improve the computational efficiency of the MATSim simulation and is explicitly focused on energy use application, as it is a Department of Energy project. One use case of BEAM has been used for electric vehicle charging demand modeling (Sheppard et al., 2017).

2.4 Current Mobility Offerings

This section discusses existing services to improve mobility for disabled individuals in the United States and other countries. Starting with a description of current mobility services around the nation involving paratransit, taxis, and TNCs, this section then paints a brief history of recent legislation regarding mobility for individuals with disabilities. The chapter ends with mobility services across the world specifically for users with wheelchairs.

2.4.1 Paratransit, Taxis, and TNCs

Residents of cities who are physically unable to use public transportation, including the disabled and mobility-impaired elderly, are offered car or van rides by paratransit services, as required by an unfunded 1990 ADA mandate (ADA, 1990). Kaufman et al. (2016) show that paratransit systems are enormous: In New York City, paratransit serves 144,000 subscribers at $456 million per year; in the Chicago region, 50,000 subscribers are served at $137 million per year; in Boston, 80,000 at $75 million per year.

In a study on meeting paratransit demand, Chia (2008) evaluated the relationship between cost and ridership. The author showed that paratransit ridership accounts for only slightly more than 1.0 percent of the total transit ridership, yet paratransit costs comprised 9.0 percent of transit operating costs. The author also showed that on average, the cost per trip of an individual is $2.75, however, the cost per trip of a paratransit ride was $22.14. For the purpose of reducing costs, there was ample opportunity for optimization strategies to be put into place. Chia shows that from the beginning of paratransit service in 1992 to 2004, paratransit ridership in the United States increased by 58.3 percent, to more than 114 million trips, most of which were ADA-complementary paratransit trips. Many transit agencies have also used taxis to assist with their required ADA paratransit service to provide a same-day service that is not officially a part of ADA paratransit service (Ellis, 2016).

2.4.2 Legislation Regarding Transportation for Users with Wheelchairs

In 2018, and in response to the growing awareness that TNCs were almost entirely inaccessible to wheelchair users, the Taxi and Limousine Commission (TLC) in New York City issued a mandate requiring Uber, Lyft and Via to make wheelchair-accessible service a growing part of their operations. While this particular mandate was not adopted, a settlement was reached in the New York State Supreme Court. The NYC TLC retained the mandate that would require TNCs to meet a wait-time requirement. As summarized by DeFazio et al. (2019), the wait-time requirement states that, by 2021, TNCs must either service at least 80.0 percent of requests for WAVs in under 10 minutes and 90.0 percent in under 15 minutes, or associate with a company that has the capacity to meet those requirements.

In September of 2018, the State of California passed SB 1376 (California, 2018) which “require[d] the Public Utilities Commission, by January 1, 2019, to begin conducting workshops with stakeholders in order to determine community WAV demand and WAV supply and to develop and provide recommendations regarding specified topics for programs for on-demand services and partnerships.” The bill also required each TNC, by July 1, 2019, to pay on a quarterly basis an amount equivalent to $0.05 for each TNC trip completed. The bill also required the commission to distribute funds to access providers, such as Lyft or Uber, that establish on-demand transportation programs or partnerships to meet the needs of individuals with disabilities.

2.4.3 Pilot Programs for Riders with Wheelchairs

Seeing the opportunity afforded by modern mobility systems (especially TNCs) and the inability of some citizens to access them, some transportation agencies have begun to explore methods to improve system access for all users. These methods have included subsidized rides, driver training programs, and others. In one notable program, the Portland Bureau of Transportation (PBOT, 2019) offers individuals with wheelchairs the opportunity to hail a WAV through their own dispatch system, connecting riders with Uber, Lyft, or other partners.

Schaller (2018), describes several cases of innovative mobility solutions for the disabled and elderly. Laguna Beach, California, for example, contracted with Uber to supplement transportation for senior and disabled passengers. The Pinellas Suncoast Transit Authority in the Tampa and St. Petersburg, Florida area, conducted a two-year pilot with multiple stakeholders including Uber, a cab company, and a wheelchair van provider for on-demand trips for individuals with travel-limiting disabilities. The Kansas City Area Transportation Authority is using taxis for same-day service for the elderly and for users with disabilities in its RideKC

Freedom program. The service schedules rides through a mobile app or through a call center. Schaller also mentions that Via – a startup company working on technologies for on-demand transit services – is developing a van service with the city of Berlin that complements existing transit service when transit may not be available such as late night and weekend travel. Schaller also highlights that TNCs have also recently started to participate in programs that supplement ADA paratransit. One example is the pilot by the Boston area transit agency that involves Uber, Lyft, and other companies. Users have the option to use any of the available providers instead of the regular ADA service. Rides can be scheduled same day (instead of the day before) and riders pay the same $2 fare. Similarly, the transit agency in Las Vegas, Nevada partnered with Lyft to provide on-demand paratransit service.

2.5 Summary

While there is evident research regarding travel patterns for individuals with general travel-limiting disabilities, little has been studied on the specific participation effects of individuals with wheelchairs. Even within the research of travel behavior of users with disabilities, there is a wide variance of conclusions, and this could be due to the lack of regularized methods of classifying disability severity in travel behavioral studies. Additionally, the existing literature has not used a regularized travel behavior modeling approach, and has rather consisted of ad-hoc studies on a variety of disconnected travel-related issues.

Within the last few years, policy has changed in New York and California so that innovative transportation solutions (i.e., TNCs) better accommodate all users, specifically including those with wheelchairs. Decisions for both changes in policy and implementation of transportation systems can be informed by simulations like MATSim and BEAM. However, a detailed simulation of services aimed at users with disabilities has never been paired with a systematic modeling of the travel behavior for these individuals. Therefore, an understanding of the effect of wheelchair use on one’s DAP choice is a relevant objective for this study.

CHAPTER 3 DAILY PATTERNS OF ACTIVITYSIM

3.1 Overview

A systematic approach to modeling a WAV system in a region requires an understanding of the daily trips taken by individuals in that region, including when they leave home, where they travel to, and what modes they are likely to use. WFRC / MAG currently use a “four-step” model to evaluate transportation infrastructure projects in their planning areas. While this model has the benefit of simplicity, it provides neither the activities accomplished by individuals nor their daily plans, making it unsuitable for examining detailed transportation behaviors and policies such as ride-hailing systems.

Activity-based models, by contrast, generate detailed and coherent DAP for individuals in a region. The ActivitySim (ActivitySim, 2021) activity-based travel modeling system was developed as an implementation of the Metropolitan Transportation Commission (MTC, the San Francisco Bay Area MPO) “Travel Model One” activity-based travel model. In this chapter, we present an implementation of this modeling framework within the WFRC / MAG planning region. This requires a consideration of the necessary inputs and then a calibration / validation exercise to transfer the model from the San Francisco region to the Salt Lake City region.

This chapter begins with a summary of the input structure of ActivitySim, including a synthetic population, a socioeconomic file, and travel model network skims. The chapter then evaluates the efforts to validate and calibrate the ActivitySim model and concludes with a post-calibration validation of the model.

3.2 Inputs to ActivitySim

This section summarizes the development of an ActivitySim implementation in the Wasatch Front region. An ActivitySim scenario requires three inputs:

- A synthetic population describing both the households and the individuals in the greater Salt Lake City metropolitan area.
- A zonal socioeconomic data file describing the locations of jobs by industry type.

- A set of travel model network skims representing the costs and travel times by all modes in each time period.

Each of these inputs will be discussed in turn in the following sections, as only a summary is necessary for this report.

3.2.1 Synthetic Population

Microsimulation-based travel models require an accurate representation of a region's population at a granular scale. Where trip-based models often represent the socioeconomic data for a zone as simply a number of households and jobs of different industries, activity-based models require more information on personal and household attributes such as age, gender, income, etc. This kind of granular data is difficult to collect and would be intrusive to privacy. A synthetic population, by contrast, is a data set that reproduces the individual and household characteristics of a region but that does not contain the specific and actual data of any real person.

Many tools for generating synthetic populations exist. In general, these synthesizers work by sampling households and individuals from a "seed" population survey to match zonal aggregate "controls." For example, the American Community Survey (ACS) Public Use Micro-Sample (PUMS) contains details on individuals and households for a 5.0 percent sample of the population, but the survey respondents can only be located within an area (called a Public Use Micro-Sample Area, or PUMA) with a population of at least 100,000. The ACS data tables, by contrast, tell how many people of different income levels and educational attainment (for example) live in each census tract, where the population is between 1,200 and 8,000. Some data, such as the number of households, might be knowable at an even smaller geographic level. A population synthesizer allows for the detailed survey responses to be accurately "projected" down to smaller geographies. PopulationSim – developed alongside ActivitySim with the assistance of AMPO – was used to create the synthetic population for this study. For this research project, the generation of the synthetic population was conducted using PopulationSim (2021), which uses an entropy maximization-based list-balancing algorithm described by Paul et al. (2018). The following sections will describe the infrastructure and construction of the PopulationSim model and includes a description of the population seed data from ACS, the controls from ACS and WFRC / MAG, a geographic crosswalk, and the validation of the synthetic population.

3.2.1.1 Population Seed from ACS PUMS

The population seed data for this research was drawn from the 2018 five-year ACS PUMS data for Utah, representing responses to the 2014 through 2018 ACS. We retain the records for persons and households residing in PUMAs in Utah, Salt Lake, Davis, Weber, and Box Elder Counties.

3.2.1.2 Controls from ACS

PopulationSim allows for controls at multiple geographic levels. The purpose of these controls is to define basic information such as the number of households of each size in a given TAZ, which the program will then try to match and assign to agents by selecting persons and households from the seed table. Table 3-1 presents the specific controls used for this study including the target data, its geographical size, the source of the data, the seed table it generates and an importance factor. These controls were adapted from an example developed by the Oregon DOT. Specific to the Salt Lake City area, these controls were derived from the ACS five-year aggregation tables at the Census tract level, with the only exception being the number of households in a zone; this was obtained from the WFRC / MAG model socioeconomic data inputs for 2019. ACS aggregation tables were downloaded using the "tidycensus" package for R (Walker et al., 2020). The "importance" value indicates how carefully PopulationSim tries to match the control target as it iteratively constructs the synthetic population in each TAZ. The high importance value given to the number of households in a TAZ indicates that the synthesizer will accurately replicate the total number of households in each TAZ and will somewhat less accurately replicate each household size. It is not always mathematically possible to match all controls perfectly, given sampling and measurement error in both the seed table and the controls data.

Table 3-1 Synthetic Population Controls

Target	Geography	Source	Seed Table	Importance
Number of Households	TAZ	WFRC / MAG	households	1000000000
Household Size 1	Tract	ACS	households	10000
Household Size 2	Tract	ACS	households	10000
Household Size 3	Tract	ACS	households	10000
Household Size 4+	Tract	ACS	households	10000
Person Age 0-14	Tract	ACS	persons	10000
Person Age 15-24	Tract	ACS	persons	10000
Person Age 25-54	Tract	ACS	persons	10000
Person Age 55-64	Tract	ACS	persons	10000
Person Age 65+	Tract	ACS	persons	10000
Household Income 1st Quartile	Tract	ACS	households	500
Household Income 2nd Quartile	Tract	ACS	households	500
Household Income 3rd Quartile	Tract	ACS	households	500
Household Income 4th Quartile	Tract	ACS	households	500
Household Workers 0	Tract	ACS	households	1000
Household Workers 1	Tract	ACS	households	1000
Household Workers 2	Tract	ACS	households	1000
Household Workers 3+	Tract	ACS	households	1000
Total Population	Region	ACS	persons	5000

3.2.1.3 Geographic Crosswalk

Because the controls are at two different geographic levels (TAZ and Census tract) and the ACS PUMS seed tables are at a third (PUMA), it is necessary to supply a geographic crosswalk to PopulationSim. This crosswalk contains a representation of the spatial relationships of TAZ, Tract, and PUMAs in the modeling region.

TAZ boundaries were imported from a GIS file provided by WFRC, while a list of the Census tracts in the five-county model area and their boundaries was created using the “tigris” package for R (Walker et al., 2020). Using this geographic information, TAZs were linked to their corresponding tracts and PUMA based on which tract contained the TAZ centroid. This centroid-in-polygon method is a simplifying assumption, as the TAZ and tract boundaries do not generally align. By definition, a tract is smaller than a PUMA and is generally completely contained within a PUMA. An investigation into using partial spatial intersections resulted in an overly complex crosswalk and substantial model run times. Figure 3-1 shows the TAZ and Census tract boundaries in Provo where we can see the incongruencies in boundary lines; we expect the consequences of this simplifying assumption are likely marginal to the accuracy of the synthetic population.

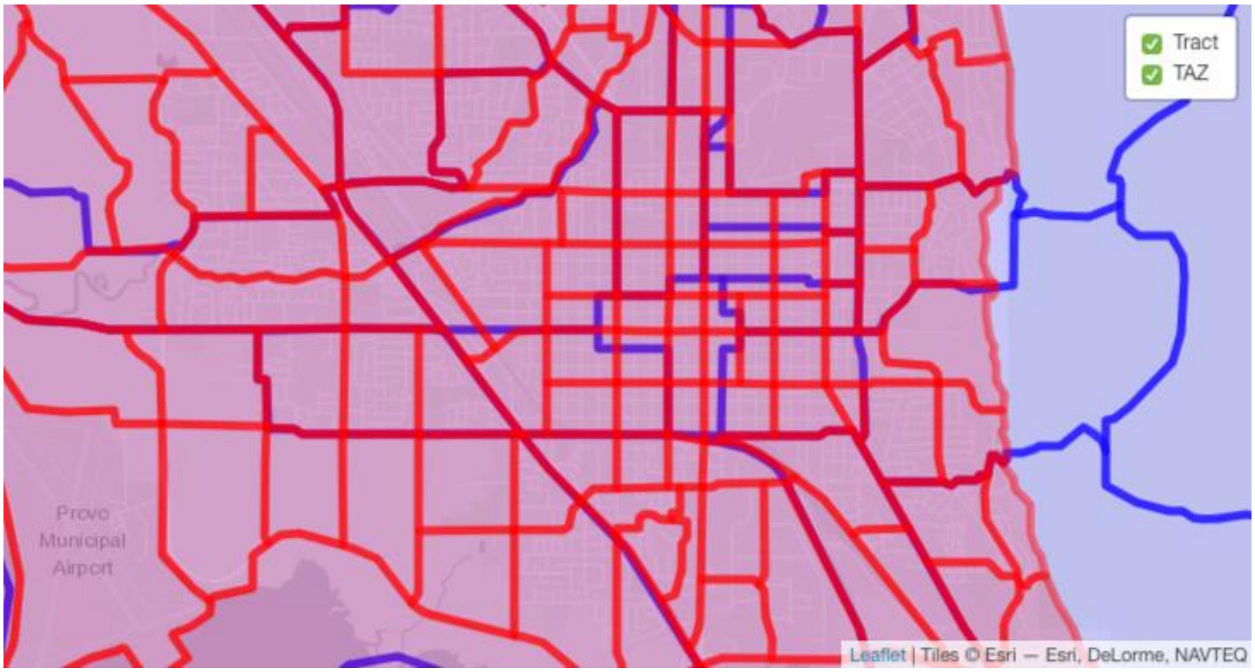

Figure 3-1 Tract (blue) and TAZ (red) boundaries in Provo, UT.

3.2.1.4 Synthetic Population Validation

After the synthetic persons and households were created, we conducted an exercise to validate that the synthetic population matched overall statistics for the region. According to the ACS five-year data for the tracts in the model area, the total population is 2.3 million individuals. The synthetic population generated 2.5 million individuals, an error of 7.4 percent. The reason for this is that the total population control parameter was generated using the 2014-2018 ACS estimates, while the total number of households in each TAZ, the highest weighted control, was taken from the 2019 WFRC model.

Figure 3-2 shows the difference between ACS tract-level population and the tract-level population controls generated by PopulationSim. In tracts shaded red, the ACS population estimate is lower than the one created using WFRC data, and vice versa for green-shaded ones. The difference between the synthetic population and the control population is greatest in the Census tracts with the highest growth rate, such as near Herriman in Salt Lake County and Vineyard in Utah County. Because of this, it was assumed that the synthetic population was still an accurate representation of the true Wasatch Front population, using 2014-2018 ACS PUMS data scaled up to match the 2019 WFRC estimates. Table 3-2 compares the distribution of the other population variables in the control data and the output synthetic population. The low margin of error on these distributions indicates that the synthetic population is a globally accurate representation of the model region.

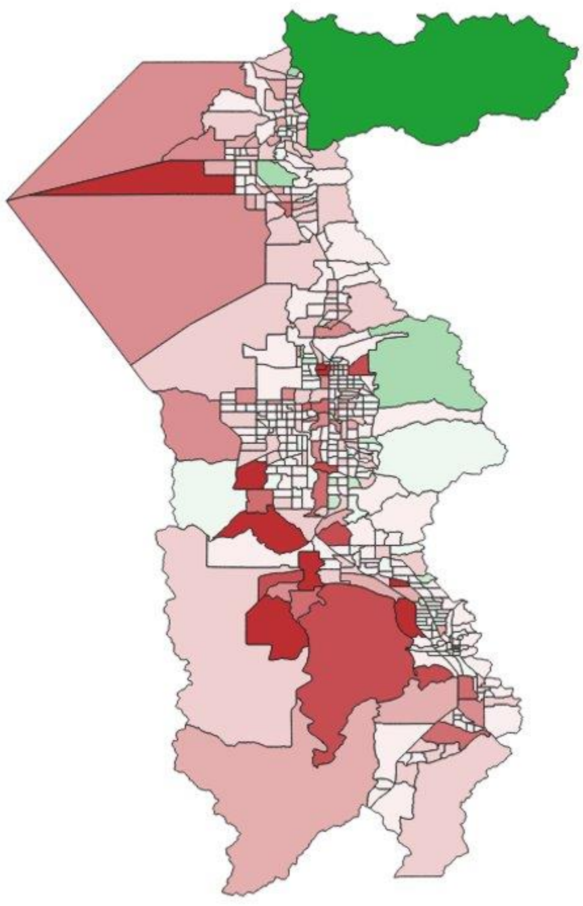

Figure 3-2 Difference between ACS and WFRC at the tract level.

Table 3-2 Synthetic Population Control Validation

Parameter	Control Population %	Synthetic Population %	Difference
Household Size 1	19.13%	19.51%	1.97%
Household Size 2	29.94%	30.53%	1.97%
Household Size 3	15.80%	15.62%	-1.14%
Household Size 4+	35.13%	34.34%	-2.25%
Person Age 0-14	25.51%	25.46%	-0.20%
Person Age 15-24	16.16%	15.97%	-1.18%
Person Age 25-54	39.67%	40.11%	1.11%
Person Age 55-64	9.14%	9.02%	-1.31%
Person Age 65+	9.52%	9.44%	-0.84%
Household Workers 0	16.90%	16.53%	-2.19%
Household Workers 1	36.52%	36.06%	-1.26%
Household Workers 2	34.52%	35.16%	1.85%
Household Workers 3+	12.06%	12.25%	1.58%

Additionally, the PopulationSim outputs were compared with the simulated joint population distributions from the WFRC 2019 base year model. The WFRC model inputs do not contain TAZ-level breakdowns of categories such as household size or workers per household, but rather generates them during the process of the model run. Because of this, household type controls were taken from the ACS data at the tract level instead. Nevertheless, during the validation of our synthetic population, TAZ-level statistics were compared to ensure that the population was comparable to the one contained in the WFRC model. The difference between the two datasets is shown below in Figure 3-3 to Figure 3-5. A positive error means that for a given TAZ there were more households of a certain type in the synthetic population than in the WFRC estimates. Because the WFRC household counts were not round numbers while the synthetic population counts were necessarily integers, the error was grouped in bins of one for the figures. Figure 3-3 shows the distribution of error between counts of households of the various income groups at the TAZ level. Household income appears to match well; in the majority of TAZs the difference was less than 25 households. There is a slight rightward skew for the first and fourth income levels, while the middle two income groups skew left, showing that these groups are respectively over- and underrepresented at the regional level by a small amount.

Household size was an even closer match between the synthetic population and the WFRC estimates. Two-person households had a slightly higher error than the other groups, while households of five or six-plus had the lowest error. As there were more two-person households in the synthetic population than any other size and because these figures display absolute error and not percent error, this result is expected.

All household worker error counts skewed left, suggesting that there was some fundamental difference between the ACS controls for workers and the way that WFRC calculates workers per household that caused a slight underestimate of total workers in our synthetic population compared to WFRC. Overall, there is a good fit between the two population estimates and using ACS tract-level controls instead of the simulated WFRC TAZ counts does not appear to have caused a drastically different household makeup.

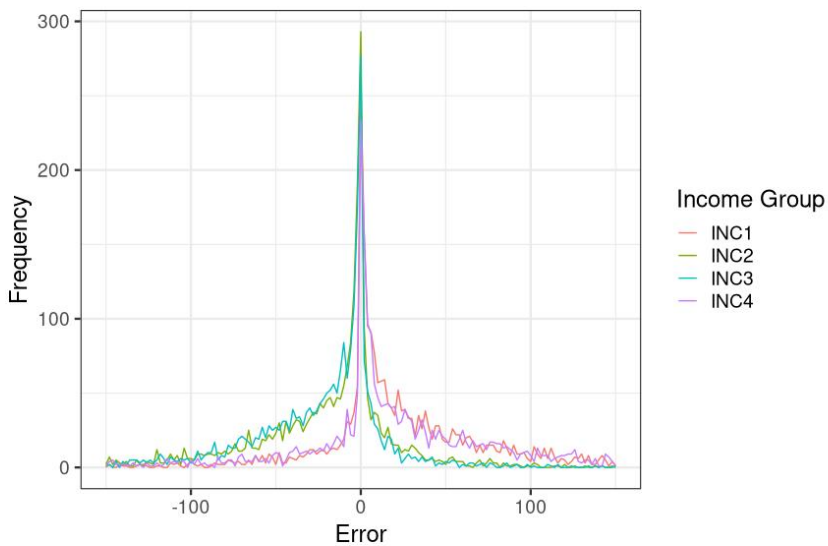

Figure 3-3 Distribution of error between PopulationSim and WFRC 2019 scenario, number of households by household income.

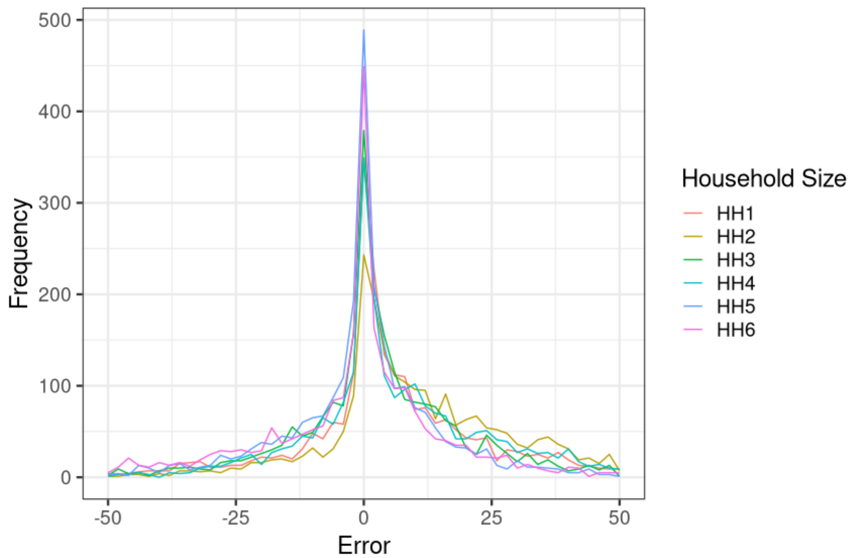

Figure 3-4 Distribution of error between PopulationSim and WFRC 2019 scenario, number of households by household size.

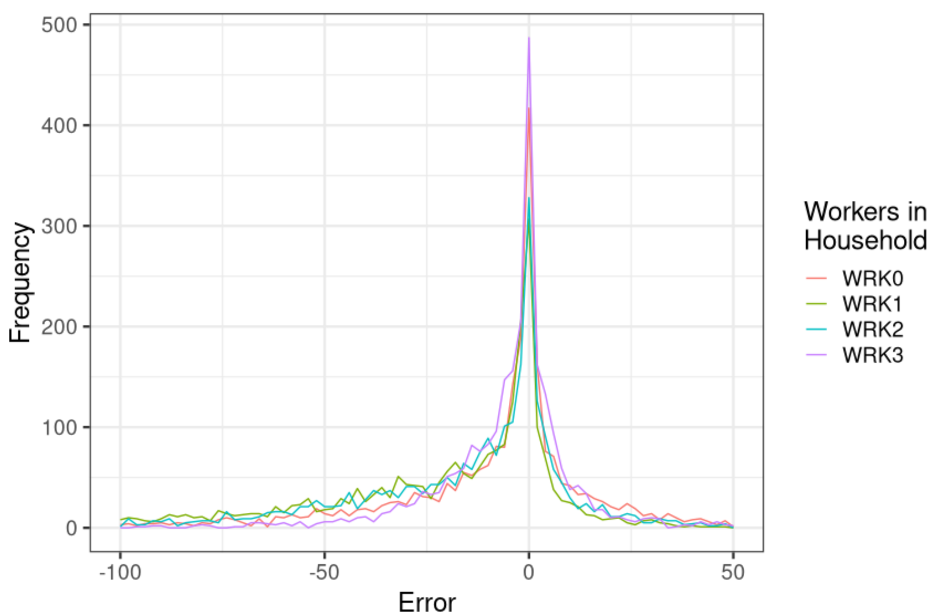

Figure 3-5 Distribution of error between PopulationSim and WFRC 2019 scenario, number of households by household workers.

3.2.2 Socioeconomic File

ActivitySim requires the input of a socioeconomic (SE) file of comprehensive zonal data. This includes specific data relating to the population, households, and land use of each TAZ. The SE file is composed of 42 different fields and was created in R. The 42 fields were extracted from and created using various data sources and tables. They were then placed in the correct order and composed into one file. The name, meaning, order, and source of each field can be seen in Table 3-3.

The definition of each name from Table 3-3 is copied directly from the Travel Model Data Dictionary under the Bay Area Metro GitHub. Most of the fields are type integer, but the Data Dictionary table can still be referenced for more specific field data types. Since ActivitySim was created originally as a template for the San Francisco Bay Area, it made sense to rely on their SE file data field setup.

Overall, the primary source of the data was gathered using tables and files from WFRC. They provided us with socioeconomic files for the TAZs of interest along with parcel, buildings, and urbanization data files as well. The WFRC SE file was useful for calculating totals regarding population, housing, and employment. The parcel and building datasets were composed of data regarding land usage, acre division, and building types. The urbanization file also had land usage data, along with parking rates. The WFRC GIS file was also used to help calculate various fields like zonal, district, and county IDs. Although WFRC provided a significant chunk of the SE data, other sources were used to calculate the missing fields.

Since WFRC did not have access to all of the data needed, the synthetic population data tables regarding persons and households were used. These tables provided the means to calculate the specific divisions of household income and persons' ages, along with the number of employed residents in each TAZ. WFRC provided data similar to this, but their categorical divisions were not the same as the needed SE file specifications. In addition to using the synthetic population data, the AGRC website was used to calculate the last remaining fields involving the topology and school information. By joining the shapefiles found on the AGRC website with the WFRC GIS file, the needed data was collected.

Table 3-3 Socioeconomic File Fields

Name	Definition	Source
ZONE	Transportation analysis zone	WFRC GIS file
DISTRICT	Super district geographic designation	WFRC GIS file
SD	Super district geographic designation(same)	WFRC GIS file
COUNTY	County	WFRC GIS file
TOTHH	Total Households	WFRC SE table
HHPOP	Population living in households	WFRC SE table
TOTPOP	Total Population	WFRC SE table
EMPRES	Employed Residents	Synthetic Population Persons table
SFDU	Number of occupied single-family dwelling units	WFRC Buildings & Parcels tables
MFDU	Number of occupied multi-family dwelling units	WFRC Buildings & Parcels tables
HHINCQ1	Households in lowest income quartile (< $30,000)	Synthetic Population Household table
HHINCQ2	Households in second lowest income quartile (> $30,000 & < $60,000)	Synthetic Population Household table
HHINCQ3	Households in second highest income quartile (> $60,000 & < $100,000)	Synthetic Population Household table
HHINCQ4	Households in highest income quartile (> $100,000)	Synthetic Population Household table
TOTACRE	Total Acres	WFRC Urbanization file
RESACRE	Acres occupied by residential development	WFRC Buildings & Parcels tables
CIACRE	Acres occupied by commercial/industrial development	WFRC Buildings & Parcels tables
SHPOP62P	Share of population >62 years old	Synthetic Population Persons table
TOTEMP	Total employment	WFRC SE table
AGE0004	Persons age 0 to 4	Synthetic Population Persons table
AGE0519	Persons age 5 to 19	Synthetic Population Persons table
AGE2044	Persons age 20 to 44	Synthetic Population Persons table
AGE4564	Persons age 45 to 64	Synthetic Population Persons table
AGE65P	Persons age 65 and older	Synthetic Population Persons table
RETEMPN	Retail trade employment	WFRC SE table
FPSEMPN	Financial and professional services employment	WFRC SE table
HEREMPN	Health, education, and recreation service employment	WFRC SE table
AGREMPN	Agricultural and natural resources employment	WFRC SE table
MWTEMPN	Manufacturing, wholesale trade, and transportation employment	WFRC SE table
OTHEMPN	Other employment	WFRC SE table
PRKCST	Hourly parking rate for long-term parkers (cents)	WFRC Urbanization file
OPRKCST	Hourly parking rate for short-term parkers (cents)	WFRC Urbanization file
AREATYPE	Area type designation	WFRC Urbanization file
HSENROLL	High school students enrolled at schools in this TAZ	WFRC SE table
COLLFTE	College students full-time at colleges in this TAZ	AGRC, WFRC, other online sources
COLLPTE	College students part-time at colleges in this TAZ	AGRC, WFRC, other online sources
TERMINAL	Average time to travel from automobile storage location to origin/destination	W FRC Urbanization file
TOPOLOGY	Topology/steepness indicator	AGRC
ZERO	Placeholder	---
HHLDS	Repeat of TOTHH field	WFRC SE table
SFTAZ	Repeat of ZONE field	WFRC GIS file
GQPOP	Population living in group quarters instead of households	WFRC SE table

Through the analyzation and manipulation of the WFRC data files, the synthetic population, and the sources found on the AGRS website, a full table of socioeconomic data was created. These fields were organized in the same way that the Bay metro area organized their table, with the same data types as well. Overall, not much information was lost throughout the process, and an accurate representation of the socioeconomic profile of all the TAZs was created.

3.2.3 Travel Model Network Skims

Finally, ActivitySim also requires network skims to model destination choice and mode choice, among other model steps. These skims contain important information about travel between every set of two zones in the region, such as travel time, distance, cost, wait time for transit modes, and so forth. The existing WFRC trip-based model already produces skims that can be configured for use in ActivitySim, though some remapping is necessary as the expected modes and day periods differ slightly between the two models. For example, the WFRC / MAG model produces initial and transfer wait time skims for transit paths; these needed to be combined as ActivitySim expects a skim for the total transit wait time.

Additionally, the ActivitySim implementation only includes internal trips; as such, the interchanges associated with external stations were removed. Finally, ActivitySim uses the "Open Matrix eXchange" (OMX) format; the team wrote a Cube Voyager script to export the WFRC / MAG skims from Cube's proprietary format to OMX. A complete mapping of the precise skims and this script are available on GitHub, but Table 3-4 presents a crosswalk of the relevant categories.

Table 3-4 WFRC / MAG and ActivitySim Skim Crosswalk

	WFRC / MAG	ActivitySim
Modes	DA – Drive Alone	SOV
	S2 – Carpool (2)	HOV2
	S3 – Carpool (3)	HOV3
	Tol_DA – Drive Alone Toll	SOVTOLL
	Tol_S2 – Carpool (2) Toll	HOV2TOLL
	Tol_S3 – Carpool (3) Toll	HOV3TOLL
	4 – Local Bus	LOC, TRN
	5 – BRT Lite (MAX)	-
	6 – Express Bus	EXP
	7 – Light Rail/Streetcar	LFR
	8 – Commuter Rail	COM
	9 – BRT (UVX)	HVY
	dist	WALK
	dist	BIKE
Day Periods	Peak	AM, PM
	Off-peak	Mid-day, Evening, Night
Variables (Drive)	ivt	TIME
	dist	DIST
	Fee	VTOLL
Variables (Drive+ Transit)	INTITWAIT+XFERWAIT	WAIT
	T4 (or T5, T6, etc.)	KEYIVT
	T4+DRIVETIME	TOTIVT
	XFARE	FAR
	DRIVETIME	DTIM
	DRIVEDIST	DDIST
	WALKTIME	WAUX
	INTITWAIT	IWAIT
	XFERWAIT	XWAIT
	BOARDINGS	BOARDS
Variables (Walk+ Transit)	INTITWAIT+XFERWAIT	WAIT
	T4 (or T5, T6, etc.)	KEYIVT
	T4 (or T5, T6, etc.)	TOTIVT
	XFARE	FAR
	WALKTIME	WAUX
	INTITWAIT	IWAIT
	XFERWAIT	XWAIT
	BOARDINGS	BOARDS
Variables (Non-motorized)	xydist	DISTWALK
	xydist	DISTBIKE

3.3 Validation and Calibration

This section will describe the motivation and process behind the validation and calibration of ActivitySim by first showing the validation of trip productions, followed by the validation of trip distribution. The section concludes with the mode choice calibration.

A four-step model generates output at each stage of the model: Trips are produced by households and businesses in each TAZ; these trips are distributed to pair up origins and destinations; the mode choice model splits these trips between modes; and the trips are then assigned to highway links and transit routes. An activity-based model works by having individuals choose whether to participate in activities, then choose which locations those activities occur at, and then which modes are used to get between them. The assignment step for an activity-based and four-step model can be the same. The goal at this stage in our research is to validate and calibrate the ActivitySim model to the Salt Lake City Area, so that trip productions, distributions, and mode choices match the given target values from the WFRC / MAG four-step travel model. There is a detailed household travel survey in Utah that could be used for validation and calibration targets; however, the most recent data collected from this survey was from 2012, making it unappealing for this purpose. The regional travel demand model has more updated information, though it is modeled and not "actual." For conciseness, the WFRC / MAG four-step model is referred to as simply the "WFRC model" in this section.

3.3.1 Validation of Trip Productions

Trip productions are an outcome of the first step in the four-step model and represent the volume of trips "produced" from certain areas – in this validation exercise we aggregate the productions to counties. Table 3-5 shows the total trip productions estimated by the WFRC four-step model for each county by trip purpose. As expected, the majority of trips are produced in Salt Lake County, and the majority of trip productions are home-based work trips and home-based other trips. The initial run of the Salt Lake ActivitySim scenario yielded similar proportions of trip productions, as shown in Table 3-6.

A challenge in comparing ActivitySim output to WFRC output was the inconsistency in trip purpose categorization between the two models. WFRC classifies trips in six different categories, while ActivitySim has 12 different categories. Additionally, the way ActivitySim and the WFRC model produce trips by purpose is fundamentally different. For these reasons, it is difficult to make a direct comparison between the two models in terms of trip purpose distribution, though the differences are not strikingly different. A better comparison is by total trips per county and percent volume per county. While the WFRC model accounts for more trips produced at each county, the distribution of trips across counties were almost identical, within variation of 1.0 percent. Another notable difference is the total number of trips produced from each county; the estimation from ActivitySim is less than the target productions estimated from WFRC by more than 200,000 trips in Davis County and by more than 400,000 trips in Salt Lake County. One hypothesis is that because the synthetic population comes from 2014-2018 data and the WFRC / MAG data comes from 2019-2020 data, the difference in years would prove to generate more trips from the newer data set from where the population is larger. Although, the annual population growth factor in Utah is only 3.0 percent. Given this hypothesis, it is also important to note that WFRC / MAG model is a trip-based model and ActivitySim is an activity-based model; therefore, there is expected to be some discrepancy in the data. This difference in volume is significant but not practical for the objectives of this report, as the relevant measure of validation is the proportion of trips for each purpose by county.

Table 3-5 Trip Productions from WFRC / MAG Regional Model

Trip Purpose	**Box Elder**	**Davis**	**Salt Lake**	**Utah**	**Weber**
Home-Based Other	43,126	542,324	1,692,979	969,068	377,782
Home-Based School	4,550	58,277	147,132	108,890	34,983
Home-Based Shopping	11,212	137,019	430,310	234,226	97,414
Home-Based Work	16,618	259,243	889,214	433,636	182,038
Non-Home-Based Non-Work	17,018	209,735	812,799	383,185	170,393
Non-Home-Based Work	8,256	98,814	460,832	182,404	80,339
Total	100,782	1,305,414	4,433,269	2,311,411	942,951
Total	1.1%	14.4%	48.8%	25.4%	10.4%

Table 3-6 Trip Productions from ActivitySim Model

Trip Purpose	Box Elder	Davis	Salt Lake	Utah	Weber
atwork	1,468	26,862	140,170	53,014	22,173
eatout	3,688	47,983	179,671	89,962	37,236
escort	8,708	83,090	283,159	173,093	60,150
Home	33,172	370,299	1,477,715	738,517	304,186
othdiscr	5,399	61,520	203,865	108,442	44,514
othmaint	5,206	62,085	220,568	109,687	48,721
school	8,554	82,003	228,816	158,315	55,388
shopping	8,613	103,081	363,713	182,702	80,096
social	2,426	24,819	89,779	47,168	20,511
univ	908	7,409	34,940	24,774	6,513
work	11,361	144,394	535,869	265,520	103,927
Work	1,452	26,616	140,513	52,947	22,159
Total	90,955	1,040,161	3,898,778	2,004,141	805,574
Total	1.2%	13.3%	49.7%	25.6%	10.3%

3.3.2 Validation of Trip Distribution

Trip distribution is the outcome of the second step of the WFRC four-step model and maps trip productions and attractions at separate locations to origin-destination pairs. The trip distributions from county to county from the WFRC model are shown as volumes in Table 3-7 and as percentages in parenthesis. For clarity, the percentages in Table 3-7 are organized by percent of trips from origin county, for example, 13.2 percent of trips from Box Elder are going to Weber. As shown, the vast majority of trips are intra-county trips, especially in Salt Lake and Utah counties. There are also high volumes of trips to neighboring counties (i.e., Davis-Weber, Salt Lake-Davis, and Utah-Salt Lake); and few trips are going beyond neighboring counties.

Table 3-7 Trip Distribution Volumes from WFRC / MAG Regional Model

Origin	Box Elder	Davis	Salt Lake	Utah	Weber
Box Elder	103,229 (81.5)	4,240 (3.3)	2,446 (1.9)	38 (0.0)	16,760 (13.2)
Davis	2,854 (0.2)	1,236,737 (76.5)	226,139 (14.0)	5,923 (0.4)	144,670 (9.0)
Salt Lake	329 (0.0)	99,716 (1.8)	5,468,782 (96.2)	109,982 (1.9)	8,934 (0.2)
Utah	9 (0.0)	11,562 (0.4)	211,470 (7.3)	2,661,490 (92.2)	975 (0.0)
Weber	12,275 (1.0)	138,013 (11.8)	36,618 (3.1)	1,504 (0.1)	985,695 (84.0)

Similarly, the trip distributions derived from the Salt Lake ActivitySim scenario show strong intra-county trips, with few trips beyond neighboring counties. Table 3-8 shows the trip distribution from county to county of the ActivitySim Salt Lake scenario as volumes and percentages in parenthesis. Comparing the volumes of WFRC and ActivitySim from Table 3-7 and Table 3-8, the majority of all trips are within Salt Lake County, however, the ActivitySim model generates only slightly more than half of the trips generated by the WFRC model. The comparison of percentages from WFRC and ActivitySim are highly similar and are accurate within 4.0 percent error across all counties. A margin of error of this size is sufficient for the validation comparison between WFRC and ActivitySim estimations of trip distribution. Overall, the trip productions and distributions from ActivitySim closely follow the target values from the WFRC model estimations. The similarities are not exact, but they are satisfactory.

Table 3-8 Trip Distribution Volumes from ActivitySim Model

Origin	Box Elder	Davis	Salt Lake	Utah	Weber
Box Elder	77,693 (85.4)	2,168 (2.4)	864 (0.9)	26 (0.0)	10,204 (11.2)
Davis	2,113 (0.2)	817,711 (78.6)	101,548 (9.8)	2,295 (0.2)	116,494 (11.2)
Salt Lake	842 (0.0)	102,004 (2.6)	3,662,886 (93.9)	121,642 (3.1)	11,404 (0.3)
Utah	22 (0.0)	2,277 (0.1)	121,676 (6.1)	1,879,722 (93.8)	444 (0.0)
Weber	10,285 (1.3)	116,001 (14.4)	11,804 (1.5)	456 (0.1)	667,028 (82.8)

3.3.3 Mode Choice Calibration

Mode choice describes how the population chooses a mode for each trip, and the WFRC model estimates are shown by purpose in Table 3-9. Work, University, and Other are the purposes selected for comparison because of commonalities between WFRC and ActivitySim output. Not shown in Table 3-9 is “single occupancy automobile,” which by far holds the largest share of mode choice and is not included because it stands as the reference alternative in the ActivitySim model – the other modes are calibrated, while the reference alternative occupies the remainder. The shared rides and non-motorized modes in Table 3-9, across all purposes, generally hold the next largest mode shares. Transit walk access for “University” trips is another notably high share from the WFRC model.

The WFRC model runs all trips through a single mode choice model. ActivitySim, by contrast, allows its individuals to first select a mode for their tour – from when they leave home to when they return – and separate modes for each trip on the tour. Tours are categorized as either "mandatory" or "non-mandatory" and are determined by the primary purpose for leaving the home. Trips on the other hand, are defined as a single event from an origin to a destination. While a trip has only one mode, a tour has one primary mode despite the many trips and modes of those trips within a single tour. Here is a simple example: One might take a bus to work, but on their walk to the bus stop, they stop at a store. Collectively this tour would be defined as a "mandatory" tour that included a shopping trip and a work trip. The mode is defined for each trip and for each tour. In this example, the first trip mode is "non-motorized" and the second trip mode is "local bus." The mode category is determined by the primary purpose of the tour and in this case would be the mode used to go to work, in this case "local bus."

ActivitySim uses choice models in a nested logit choice model tree, as shown in Figure 3-6, to determine the mode choice for each tour and each trip. The tour modes are broken into auto, non-motorized, or transit nests for each purpose. As part of the auto nest, shared-ride of two individuals and shared-ride of three or more individuals are the available modes, and single occupancy rides is the reference alternative, where the coefficient is zero. Non-motorized modes are either walk or bike but are summarized into one coefficient as non-motorized to match the mode share categories of the WFRC model (there is no walk or bike distribution available from WFRC). The third nest is transit and is either walk transit or drive transit by various transit modes including local bus, express bus, commuter rail, light rail, and heavy rail (heavy rail is also not available in the WFRC model).

Similar to the trip production validation exercise, there was also the challenge of inconsistent mode categories between the two frameworks: The WFRC model includes 10 trip mode choices, according to Table 3-9. ActivitySim does include the same 10 *tour* mode choice categories, as shown in Table 3-10, while ActivitySim includes only five of those trip mode choices, as shown in Table 3-11. Because of the complexity of the relationship among ActivitySim's choice models, the selection of mode then influences the available and likelihood of choices of trips within each tour. For this reason, both trips and tours from ActivitySim are considered.

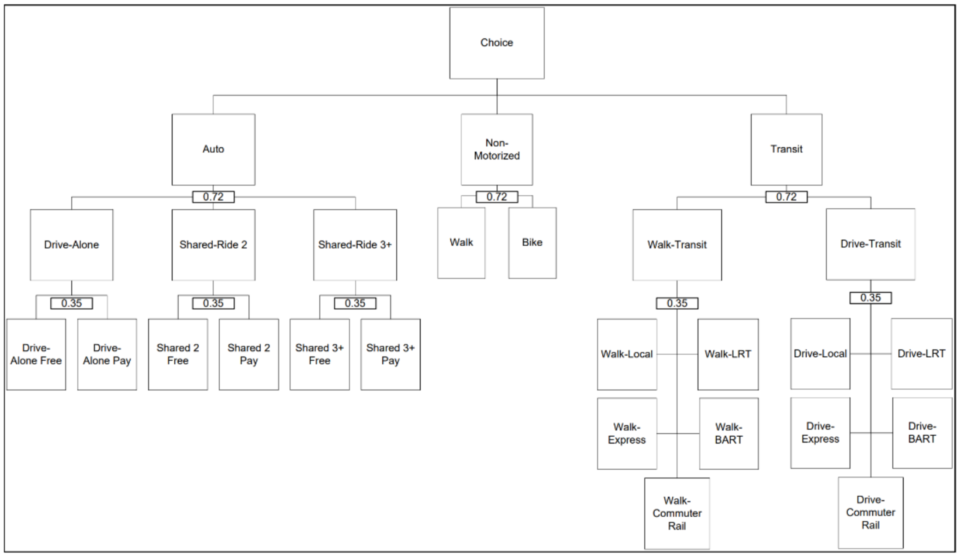

Figure 3-6 ActivitySim nested logit choice model structure (MTC, 2012, p. 100).

From the WFRC model, as shown in Table 3-9, the shared rides and non-motorized modes comprise the largest split; of these mode choices, there are large differences when compared to the ActivitySim output in Table 3-10 and Table 3-11. ActivitySim underrepresents non-motorized trips for university and other trips and overrepresents non-motorized work trips. ActivitySim also underrepresents shared rides across all trip purposes. There is also a large difference in commuter rail for work tours and in local bus for all tour purposes; ActivitySim largely overrepresents these trips too. While the WFRC model and the ActivitySim model for Salt Lake City show comparable trip productions and distributions, the mode choice does not satisfy our requirements and requires calibration.

Table 3-9 Mode Choice of Trips from WFRC / MAG Regional Model

Mode	Work	University	Other
Express Bus	0.08%	0.08%	0.00%
Commuter Rail	0.92%	3.34%	0.10%
Non-Motorized	4.67%	17.56%	11.32%
Shared Ride (2)	9.90%	10.55%	23.04%
Shared Ride (3+)	5.85%	5.64%	34.79%
Local Bus	0.94%	5.96%	0.33%
Light Rail (Walk)	1.15%	4.00%	0.39%
Light Rail (Drive)	0.19%	1.27%	0.02%
Transit Walk Access	2.85%	16.42%	0.87%
Transit Drive Access	0.57%	3.49%	0.05%

Table 3-10 Mode Choice of Tours from ActivitySim Pre-Calibration

Mode	Work	University	Other
Express Bus	0.03%	0.32%	0.11%
Commuter Rail	4.37%	3.72%	0.62%
Non-Motorized	7.95%	8.42%	19.64%
Shared Ride (2)	11.85%	3.40%	19.69%
Shared Ride (3+)	6.93%	3.56%	21.39%
Local Bus	15.71%	41.78%	10.91%
Light Rail (Walk)	4.22%	5.59%	1.98%
Light Rail (Drive)	0.59%	0.49%	0.10%
Transit Walk Access	20.94%	47.94%	13.26%
Transit Drive Access	3.99%	3.97%	0.47%

Table 3-11 Mode Choice of Trips from ActivitySim Pre-Calibration

Mode	Work	University	Other
Express Bus	0.05%	0.23%	0.08%
Commuter Rail	2.60%	2.45%	0.40%
Non-Motorized	10.40%	11.50%	21.08%
Shared Ride (2)	7.77%	4.15%	18.80%
Shared Ride (3+)	3.22%	1.90%	15.68%

To calibrate ActivitySim such that mode choice by purpose matches the target mode choice from the WFRC model, the alternative-specific constants need to be adjusted inside the choice models of ActivitySim for both tours and trips. The utility function for individual n choosing a particular mode i can be expressed as outlined in Equation 1.

$$V_{ni} = \alpha_i + \beta_i X_{ni} \tag{1}$$

Where α_i is an alternative-specific constant, X_{ni} is a vector of mode attributes (e.g., travel time and costs), and β_i is a vector of estimated coefficients. These coefficients determine the likelihood of each agent's choice of mode choices by purpose in the simulation. It is known (see Train, 2009) that that the overall mode share resulting from a choice model is determined by the values of the α_i constants for each mode, and that any resulting bias can be adjusted using Equation 2.

$$E(\alpha_i) = \hat{\alpha}_i + \ln\left(\frac{A_i}{S_i}\right) \tag{2}$$

Where the biased alternative-specific constant $\hat{\alpha}$ for a particular mode i can be adjusted by a factor to obtain the expected true value $E(\alpha)$. The target mode share of the WFRC model is represented by A and the given, modeled mode share from ActivitySim is represented by S. Thus, $\ln(\frac{A}{S})$ becomes a correction value that improves the estimate of α to an estimate that better reflects the Salt Lake region.

The ActivitySim model was calibrated by changing both the tour mode choice coefficients and the trip mode choice coefficients for each purpose over several iterations. This calibration took five iterations to approximate the target mode choice values from WFRC for each purpose. The results from the tour calibration and trip calibration are shown in Figure 3-7 and Figure 3-8, respectively. These figures show dotted lines representing the target values (from WFRC) and solid lines representing the simulated value and their improvement over the five iterations. Notice how the solid line, the simulated value, approaches the target values for each mode by each purpose. The values that stray the most from the target are of the "University" purpose and "local bus" mode. This error could be caused by a mixture of "school" and "university" coefficients (these are unique categories in the ActivitySim model, however, the

WFRC model only includes “university”). To minimize this error, we identified agents in ActivitySim over the age of 18 taking school trips and labeled them as “university students.” The error summary of both tours and trips are shown in Table 3-12 and Table 3-13, respectively. The final mode choice values by purpose vary from the target mode choice values by a maximum error of 5.3 percent of tours, according to Table 3-12, across all modes and 4.3 percent of trip modes, according to Table 3-13. This is an acceptable margin of error to continue in the research as the average error across all modes for both tours and trips is less than 1.5 percent.

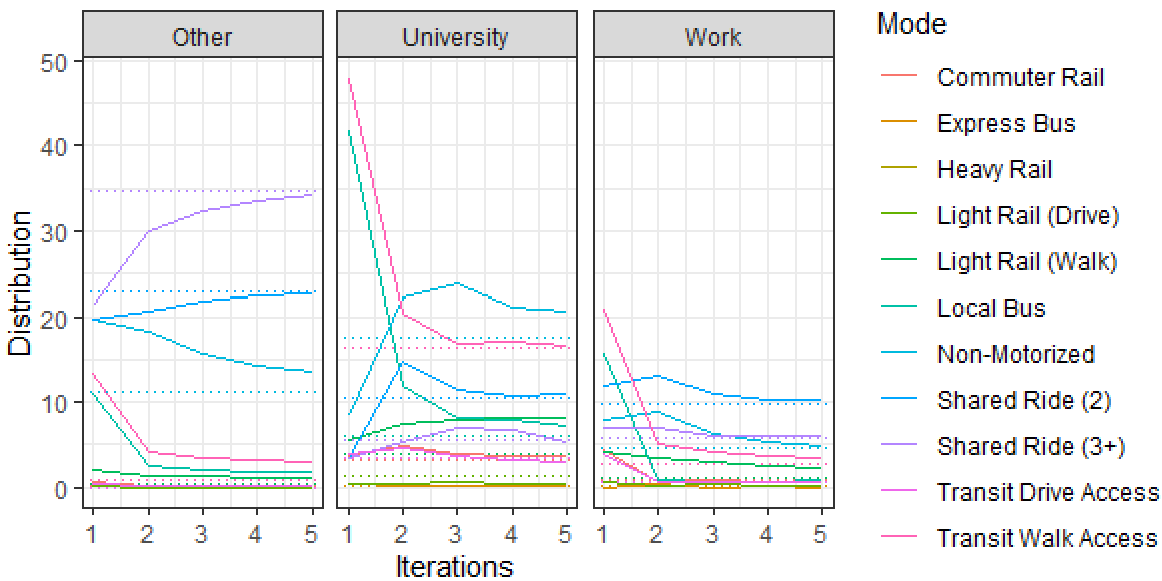

Figure 3-7 Tour mode share calibration; WFRC model target at dotted line.

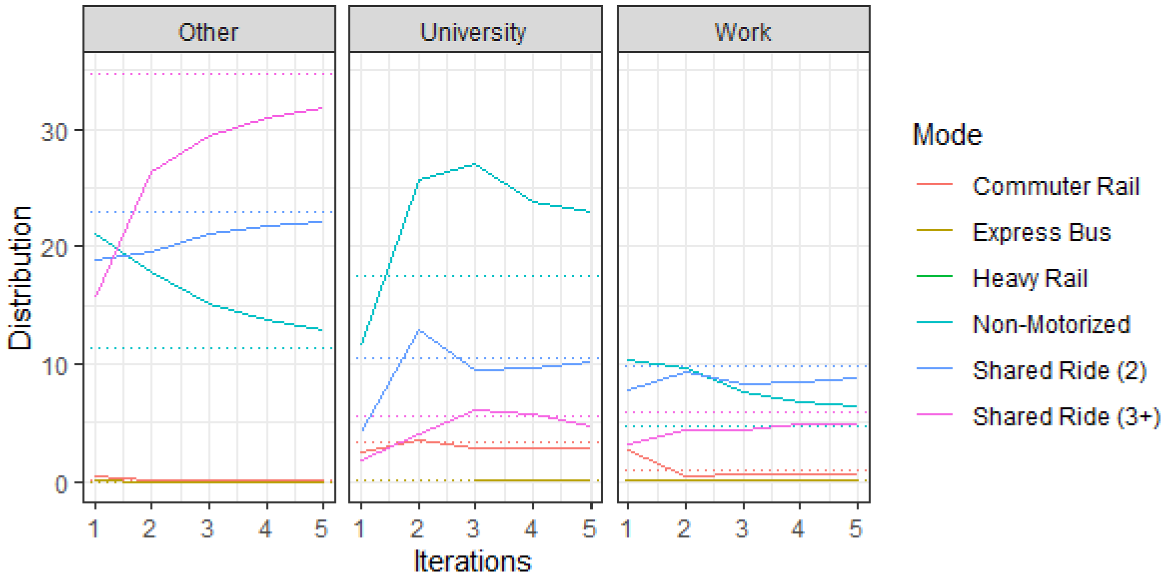

Figure 3-8 Trip mode share calibration; WFRC model target at dotted line.

Table 3-12 Estimated Error of Tour Mode Share Calibration

Iteration	Maximum	Average	Standard Deviation
1	35.82	6.32	8.99
2	6.87	3.77	2.39
3	6.27	2.35	1.71
4	4.17	1.59	1.20
5	4.25	1.20	1.04

Table 3-13 Estimated Error of Trip Mode Share Calibration

Iteration	Maximum	Average	Standard Deviation
1	19.11	3.76	4.68
2	8.36	2.44	2.83
3	9.59	1.78	2.43
4	6.31	1.24	1.61
5	5.3	1.06	1.31

3.4 Post-Calibration Validation

After calibrating the mode choice models, a final validation was necessary to verify that productions and distributions from the ActivitySim model did not vary from its original outputs on the other model steps. We found that trip productions and distributions saw minimal changes. Table 3-14 shows the trip productions from ActivitySim after its calibration, and the change in volume is less than 0.1 percent from each county when compared to the pre-calibration values in Table 3-6.

Table 3-14 Trip Productions Post-Calibration from ActivitySim

Trip Purpose	Box Elder	Davis	Salt Lake	Utah	Weber
atwork	2,122	30,021	154,549	56,096	22,958
eatout	4,085	51,439	190,920	94,190	39,149
escort	9,442	88,720	302,936	181,024	63,261
Home	35,416	376,254	1,473,780	737,251	303,164
othdiscr	5,624	63,289	211,084	110,978	46,060
othmaint	5,789	66,462	235,977	114,448	51,128
school	8,600	81,886	229,201	157,956	55,556
shopping	9,629	110,446	389,842	190,963	84,295
social	2,607	26,891	96,139	49,254	21,471
univ	901	7,538	34,484	25,117	6,545
Work	13,614	176,665	699,595	322,451	127,402
Total	97,829	1,079,611	4,018,507	2,039,728	820,989
Total	1.2%	13.4%	49.9%	25.3%	10.2%

Trip distribution from the ActivitySim model also shows minimal difference from before calibration. This is to be expected, as the change in mode does not change the likelihood of an agent taking a trip. Table 3-15 shows the volumes and percentages post-calibration from ActivitySim. It is clear that trip distributions see minimal changes from pre-calibration, as shown in Table 3-8.

Table 3-15 Trip Distribution Volumes Post-Calibration from ActivitySim

Origins	Box Elder	Davis	Salt Lake	Utah	Weber
Box Elder	84,655 (86.5)	2,191 (2.2)	602 (0.6)	25 (0.0)	10,356 (10.6)
Davis	2,125 (0.2)	857,084 (79.4)	100,412 (9.3)	2,361 (0.2)	117,629 (10.9)
Salt Lake	578 (0.0)	100,884 (2.5)	3,776,825 (94.0)	130,620 (3.3)	9,600 (0.2)
Utah	22 (0.0)	2,482 (0.1)	130,496 (6.4)	1,906,405 (93.5)	323 (0.0)
Weber	10,449 (1.3)	116,970 (14.2)	10,172 (1.2)	317 (0.0)	683,081 (83.2)

3.4.1 Trip Length Frequency

Trip length frequency shows the length of trips, in miles, of a population by mode and the frequency of that trip length and is another method of validating the model. Trip length frequency plots can be used to compare the trip-making behavior of the individuals of a population and further validate the ActivitySim model. Here trip length validation is shown for each mode category: automobile, transit, and non-motorized, and for each mode within those categories.

The automobile mode choice category is made up of three different modes: drive alone free, shared ride (2), and shared ride (3+). As shown, ActivitySim underrepresents the frequency of trips under 3 miles in each category, and slightly overrepresents trips between 3 and 10 miles. For all groups in the automobile category, the comparison is acceptable and sufficiently represents the trip-making behavior of the WFRC model for the purposes of this research, although there are fewer trips from ActivitySim than trips from WFRC, as shown by the red line in the figures. While “auto” represents the general class of automobile ridership, “Drivealonefree” represents ridership of a single person, “shared2free” represents the ridership from carpool trips of two persons, and “shared3free” represents carpool trips of three or more persons.

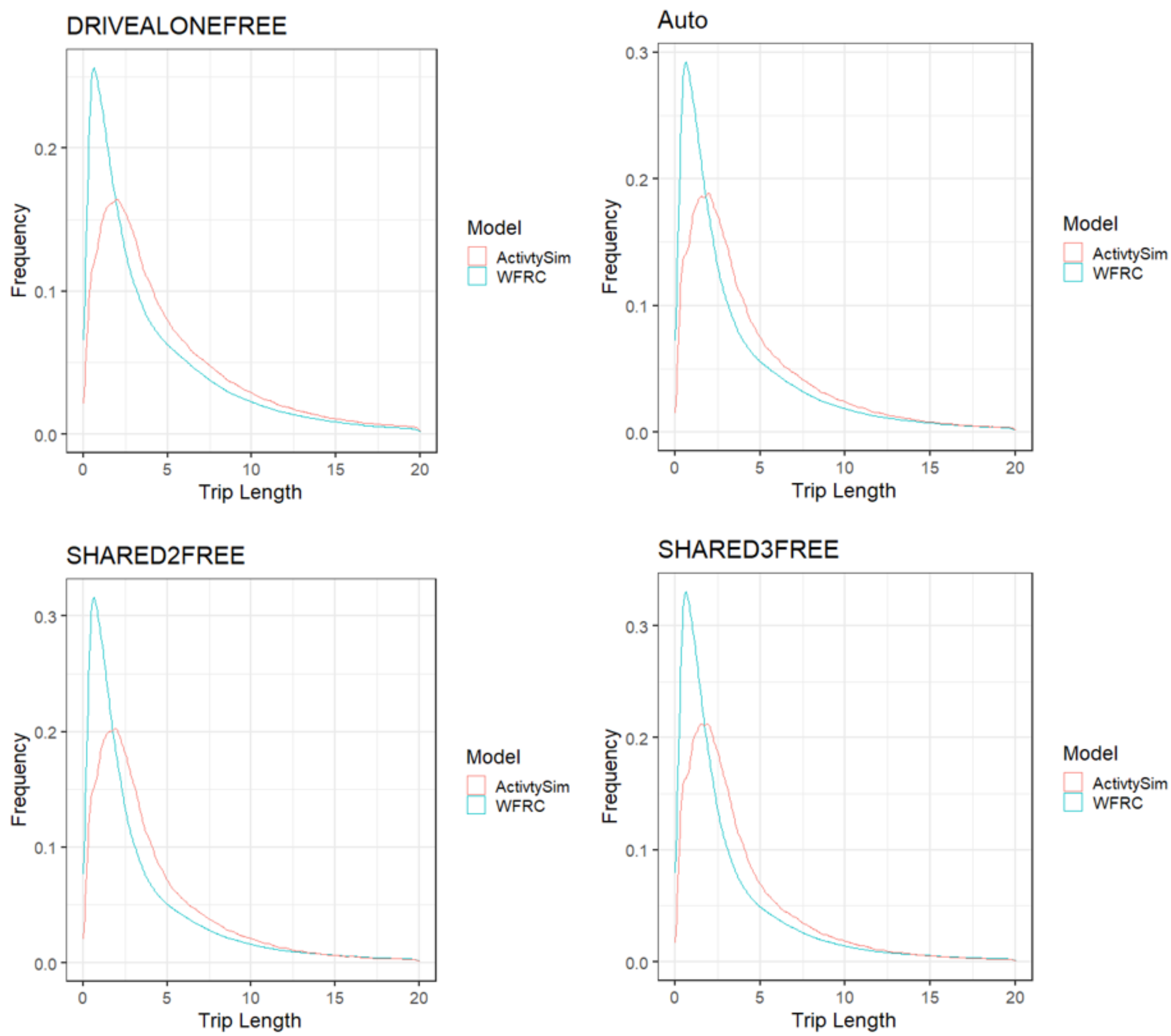

Figure 3-9 Trip length frequency charts for automobile modes.

In each of the four transit mode choice categories in the two models, there are agents who "walk" or "drive" to those transit modes; thus, there are a total of eight transit mode choice groups that are compared in the "transit" branch of the mode choice model tree: commuter rail (drive and walk) represented by "com" in these figures, express bus (drive and walk) represented by "exp," local bus (drive and walk) represented by "loc," and light rail (drive and walk) represented by "lrf."

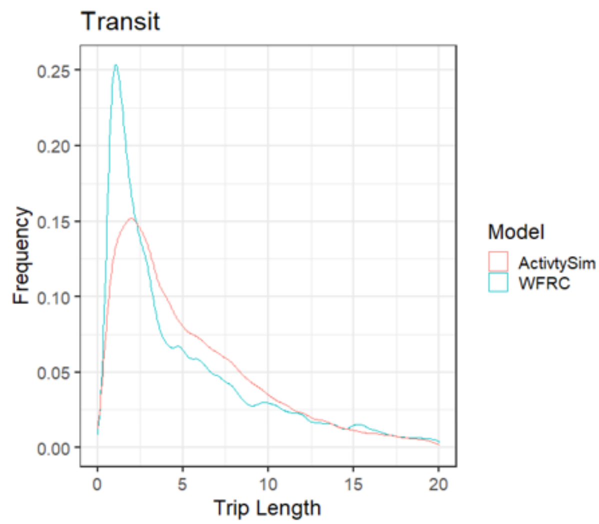

Figure 3-10 Trip length frequency chart for general transit.

In the overall transit category shown in Figure 3-10, ActivitySim underrepresents transit for trips less than 3 miles and overrepresents transit in trips between 3 and 10 miles. Specifically for commuter rail (see "drive to transit" in Figure 3-11 and "walk to transit" in Figure 3-12), ActivitySim underrepresents trips less than 10 miles for agents who drive to the mode, and underrepresents trips above 10 miles for those who walk to the mode. In a general sense, ActivitySim tends to overestimate longer trips for those who drive and underestimate longer trips for those who walk, and this trend is reversed for shorter trips. ActivitySim generally underrepresents short trips for those who drive. Considering agents who walk to commuter rail, ActivitySim closely approximates trips less than 10 miles. The express bus was more difficult for ActivitySim to estimate and shows some discrepancy. For trips above 20 miles on the express bus, ActivitySim overrepresents agents who drive and underrepresents agents who walk. WFRC models the express bus with distinct peaks that represent the specific trips that the express bus provides specific to the Salt Lake Area. ActivitySim models a more general trend of trips on the express bus, both for those who drive and walk, and though different, ActivitySim estimates the trips with an accuracy sufficient for this research purpose.

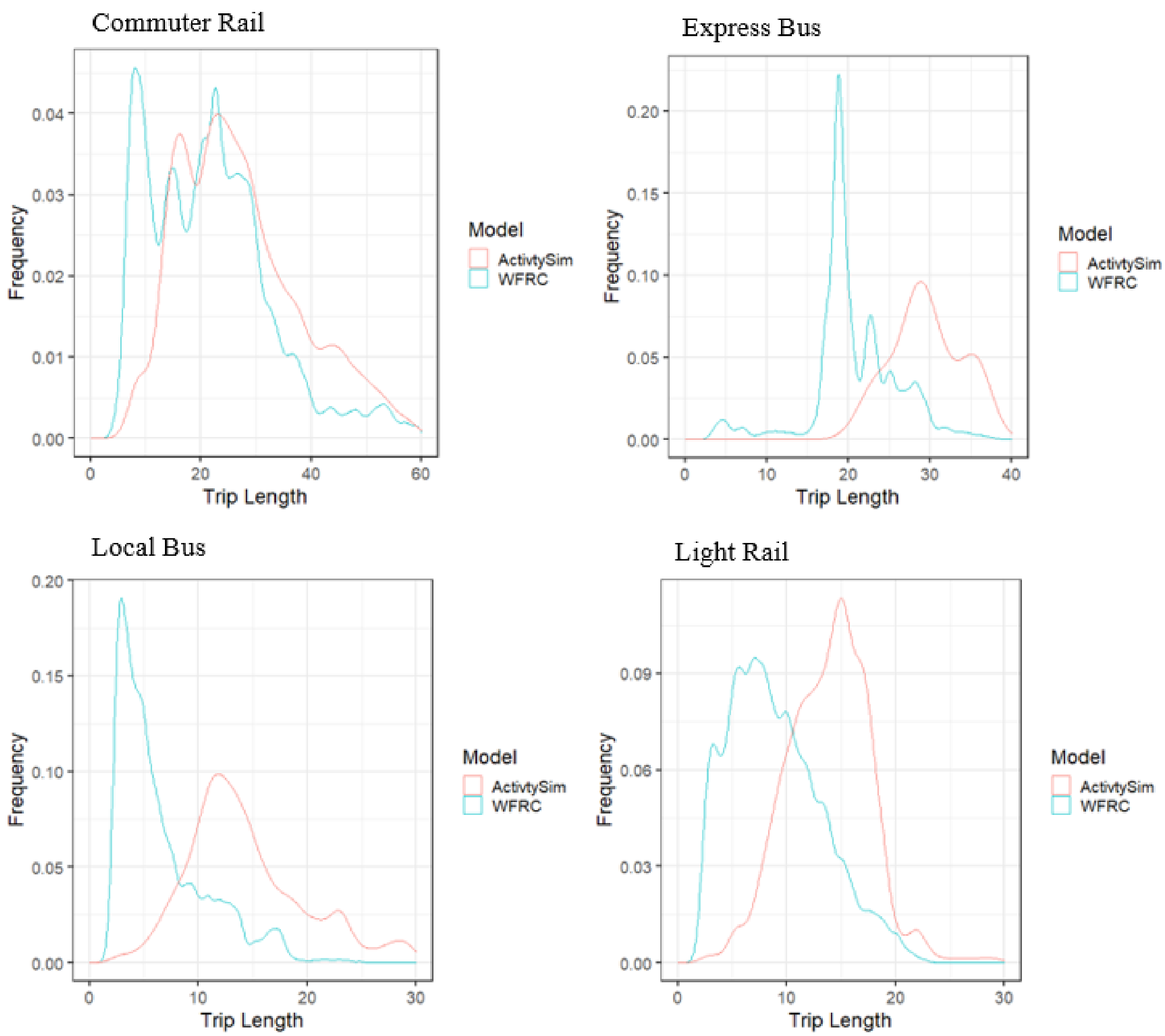

Figure 3-11 Trip length frequency charts for "drive to transit" modes.

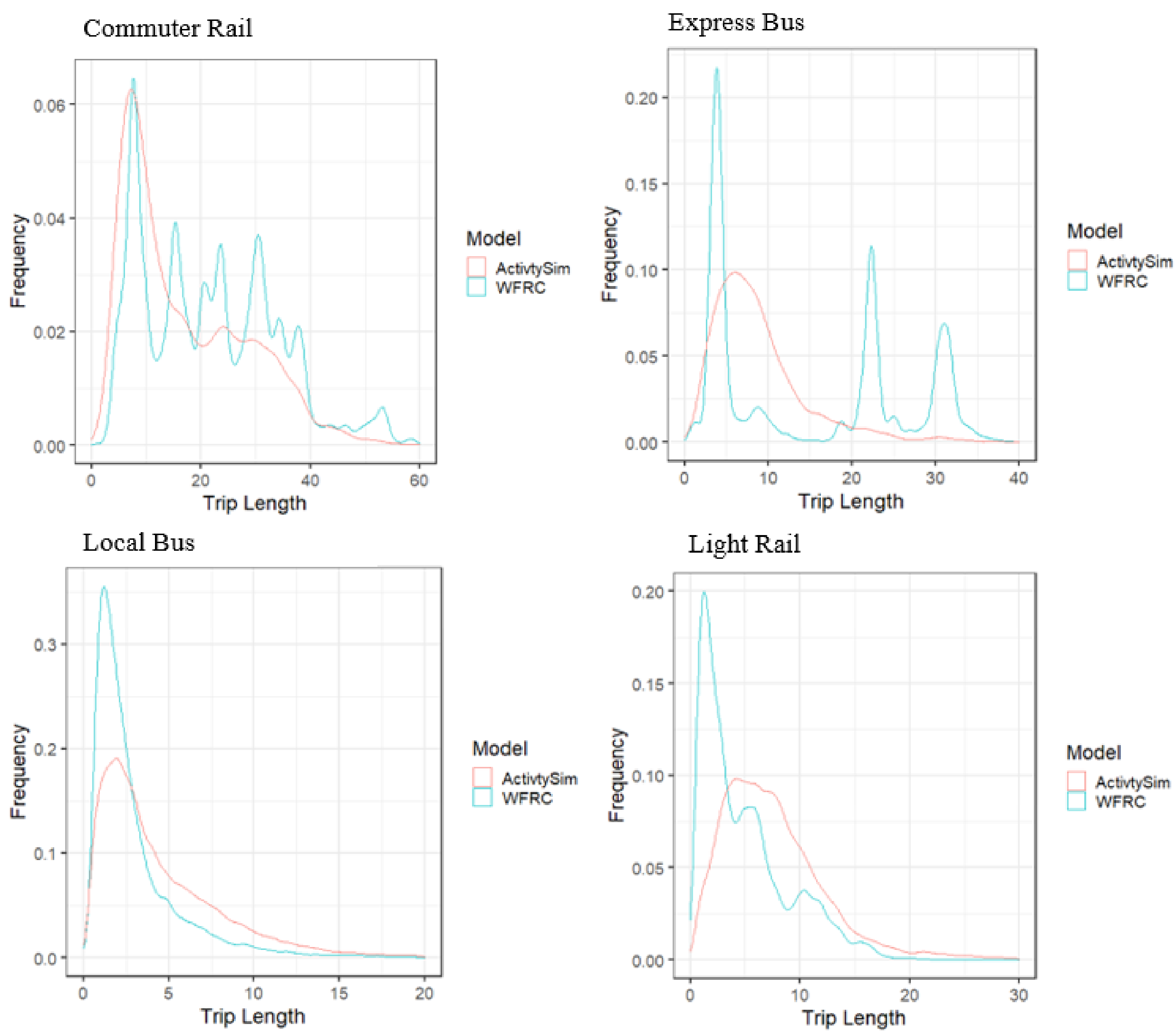

Figure 3-12 Trip length frequency charts for "walk to transit" modes.

ActivitySim also represents well the non-motorized share of trips in the trip length frequency validation, as shown in Figure 3-13. The trips of lengths less than 1 mile are slightly underrepresented by ActivitySim, while trips of length between 1 and 3 miles are slightly overrepresented. This difference is negligible for our research purposes, though further calibration could result in more accurate models.

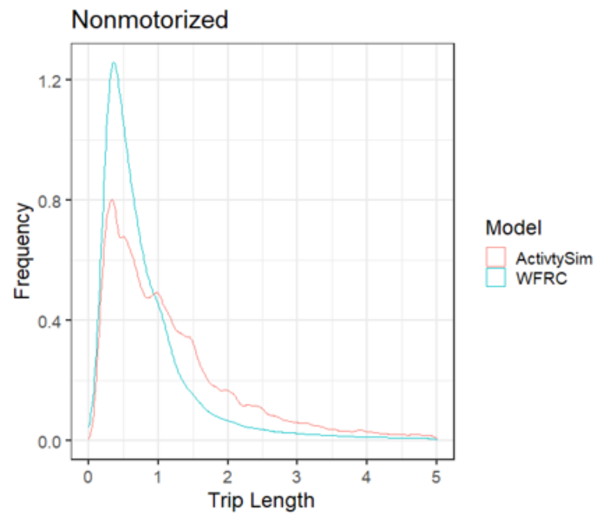

Figure 3-13 Trip length frequency chart for non-motorized modes.

3.5 Summary

As the objective of this research is to first understand the effect of wheelchair use on one's choice of DAP and second to use that understanding to model a WAV system, the purpose of this project is not to create a model that can be used by WFRC / MAG for infrastructure alternatives analysis. Consequently, the calibration efforts reported in this chapter aim to adjust the ActivitySim model so that it produces a reasonable picture of realistic trips in the Wasatch Front Region. A "true" calibration exercise would generate new survey targets from the most recent household travel survey and aim to faithfully reproduce those targets with the model; that level of effort is outside the scope of this research.

This chapter described the inputs required by ActivitySim and discussed the process of validation of trips productions, distributions, and mode choice from the ActivitySim model with the target values from the WFRC / MAG trip-based travel-demand model. We found that without any calibration, ActivitySim produced reasonable allocation of trips by purpose and by county for both trip productions and distributions. The mode choice models, however, required calibration. These were calibrated by adjusting the choice alternative-specific constants within the tour mode choice and the trip mode choice models. After calibration, the "reasonable"

ActivitySim model proves useful in generating DAP for the synthetic population of the Salt Lake Area.

As was mentioned, the calibration of the model was based primarily on mode choice, but it could be improved and calibrated on other metrics such as trip length distribution or trip origin / destination. The target values from WFRC / MAG used for calibration were generated from their four-step model and not from observed data. While our methods of calibrating the ActivitySim model to the Salt Lake Area were sufficient for the limited purposes of this project, more robust calibration would be necessary were this model to be used for infrastructure policy analysis by the regional planning agencies.

Considering Figure 1-1, this chapter provided context and understanding of the necessary validation and calibration of ActivitySim. On this foundation, we can move forward to consider the DAP of individuals who use wheelchairs, and how they inform the choice models of ActivitySim.

CHAPTER 4 DAILY PATTERNS OF WHEELCHAIR USERS

4.1 Overview

This report has to this point discussed the set up and validation of the activity-based model, ActivitySim and its implementation to a custom scenario in Salt Lake City. This background has set the stage for a primary contribution of this research: to understand the effect of wheelchair usage on one's choice of DAP. The process of measuring the effect of wheelchair usage will be discussed in this chapter.

Virtually all travel demand models have different model parameters for persons of different types. This allows, for example, for full-time workers to have different modeled daily activity patterns and trip distribution characteristics than non-workers or children. This categorization of types of persons based on their generic behavior will be referred to as *person-types.* Within specific person-type segments, certain variables such as age, gender, or income may provide additional sensitivity or accuracy in these behavior models.

Despite the literature researching differences in travel patterns within the community of individuals with disabilities, as discussed in Section 2.2, we have found no extant regional travel demand models that include disability status as either a separate person-type segment or as a modifying variable in travel behavior. To realistically simulate the daily activity plans of wheelchair users within the WAV simulation, it is necessary to obtain estimates for travel behavior model parameters for these users, and how these parameters differ from the non-wheelchair-using population.

This chapter first presents an examination of the DAP of wheelchair users in the 2017 NHTS. Next, this chapter shows the modeling and estimation of DAP, using a multinomial logit framework. Then the chapter covers the application of the estimated DAP model coefficients in the ActivitySim scenario for the Wasatch Front Region. Finally, this chapter covers the DAP analysis, discussing the individual, household, and aggregate change in estimated travel resulting from including wheelchair status in the model.

4.2 Examination of Daily Patterns in NHTS

The first model in the ActivitySim model chain is a DAP model of the type described by Bradley and Vovsha (2005). This model allows individuals to choose one of three daily activity patterns:

- Mandatory daily patterns revolve around school and work activities that are typically considered non-discretionary. These activities and the travel to them anchor an individual's daily schedule, though other tours are possible.
- Non-Mandatory daily patterns involve only discretionary activities: shopping, maintenance, etc.
- At-Home daily patterns describe the schedule and activities of individuals who never leave home during the travel day.

To study the DAP of individuals, we obtained survey responses from the 2017 NHTS. The data is restricted to households where the metropolitan statistical area (MSA) population size is between one and three million people, as individuals in these areas will travel most similarly to individuals in the Salt Lake City metropolitan area. There are 34,817 individuals in 18,773 households that responded to the NHTS from these areas. The NHTS data are distributed for public use in four tables:

- a "Persons" table describes the attributes of all persons responding such as age, gender, and if they have a travel-limiting disability;
- a "Households" table with attributes of each household such as income and auto ownership;
- a "Trips" table with attributes of each persons' trips such as mode, duration, purpose and length; and
- a "Vehicles" table which is not used in this study.

Understanding the DAP for a given individual requires a list of their activities for each tour, and not simply a list of the trip purposes as provided. From the trips table, we derived activities with start time, end time, duration, and locations. These activities were chained together to create daily tours of individuals and joined person and household attributes to these tours. Each tour was identified as “mandatory,” “non-mandatory,” and “home.” If any tour contained a “mandatory” activity, the person’s entire DAP was classified as “mandatory,” if not, the DAP was “non-mandatory.” By identifying respondents in the persons table without records in the trips table, they were assigned a “home” daily activity pattern.

ActivitySim classifies persons into seven person segments, though we only consider four segments in this study, defined as follows:

- Full-time workers - reported working “full time” at their primary job.
- Part-time workers - reported working “part time” at their primary job, as well as any person who reported being a “non-worker” or “retired” who nevertheless reported a work or school activity.
- Non-working adults - reported “unemployed” as their primary activity of the previous week, as well as individuals over 18 who were not classified elsewhere.
- Retired - reported “retired” as their primary activity of the previous week, or who are over the age of 65 and reported that they were not workers.

The other three person types are university students, schoolchildren under driving age, and driving-age schoolchildren. A limited number of individuals who could plausibly be considered university students responded to the NHTS, so we cannot estimate reliable choice models. Among schoolchildren of any age, too few report using wheelchairs to justify including these segments in this study.

The NHTS also contains responses to questions that allow us to infer wheelchair use for respondents. There are questions where respondents can indicate a disability for themselves or other household members. Each respondent is asked “Do you have a condition or handicap that makes it difficult to travel outside of the home?” If the answer is yes, several follow-up questions are asked, including “Do you use any of the following medical devices? Select all that apply.” The list of medical devices respondents can indicate includes canes, walkers, seeing-eye dogs, crutches, motorized scooters, manual wheelchairs, motorized wheelchairs, or something else (other). For this study, wheelchair users are identified as respondents who report using a manual wheelchair, mechanical wheelchair, or motorized scooter.

The DAP summary by person type in Table 4-1 shows the frequency of DAP chosen by NHTS responses for each ActivitySim person type, plus wheelchair users. These data show that wheelchair users choose a “mandatory” or “non-mandatory” DAP, more frequently than a “home” DAP. However, there is a larger percentage of wheelchair users that choose a “home” DAP when compared to full-time workers and non-workers. While some wheelchair users behave similarly to full-time workers, part-time workers, non-workers, or retired person type groups, the models used for estimation do not consider “Wheelchair User” as a distinct person-type segment, rather a wheelchair use variable for the existing person types is used in modeling and estimating DAP from the NHTS data source.

Table 4-1 Daily Activity Pattern Distribution by Person Segment

Person Type	Home	Mandatory	Non-Mandatory
Full-Time Worker	1,419	10,076	4,414
Part-Time Worker	1,117	0	2,535
Non-Worker	428	2,305	1,478
Retired	2,271	0	6,800
Wheelchair User	103	311	154
Driving Age Student	143	455	235
Pre-Driving Age Student	309	18	246
Total	5,790	13,165	15,862

4.3 Modeling, Estimating DAP from NHTS

The purpose of our estimation modeling research is not to identify a definitive best fit model of activity pattern choice for each person type, but rather to provide a realistic estimate of the effect that wheelchair use has on DAP. Using a multinomial logit model (Train, 2009), we estimate the DAP of individuals accounting for income categories, age categories, gender, education, work-from-home status, and wheelchair use for each of the person-type segments. While it was considered to use wheelchair users as a segmented person type to more accurately model their behavior, the practice of using wheelchair as a variable in the existing person-type segmentation proved equally significant. An alternate analysis considering wheelchair users as an independent person-type segment is described in greater detail in Appendix A.

We estimate the models using the mlogit software for R (Croissant, 2019; R Core Team, 2020). Table 4-2 presents the estimated model coefficients and shows each of the variables used in the model among each of the person-type models according to both “mandatory” and “non-mandatory” DAP. In these models, the home DAP is the reference alternative; coefficients indicate the additional utility (or disutility) contribution from that variable relative to choosing home. Additional variables – including auto ownership for full-time workers – proved insignificant and are omitted. The signs of each coefficient are to be expected, though not all are significant. For instance, full-time workers in the middle two income groups are less likely to choose “non-mandatory” patterns (the lowest income group is the reference and is equal to zero), and part-time workers of higher income are less likely to choose “mandatory” patterns. Income appears to have no discernible effect on the choices of non-working and retired individuals. Indeed, wheelchair use is among the strongest predictors of DAP choice across population segments. We see a negative utility score for all person types with a wheelchair variable, and “mandatory” is even more negative. This is expected as individuals with wheelchairs are less likely to take a work or school trip compared to a shopping or a recreational trip. Non-workers and retired person types do not have a coefficient for “mandatory” DAP because those users by definition do not take “mandatory” DAP.

The key coefficients to observe in Table 4-2 are in the highlighted row labeled “Wheelchair Use.” These coefficients determine the choices of the person type. Notice that all person types have both negative and significant coefficients on wheelchair use. This shows that all person types with wheelchair status are significantly less likely to have a “mandatory” or “non-mandatory” DAP, and that wheelchair users that are retired are also less likely to leave the home.

Table 4-2 Model Estimation Results

	Full-Time Worker	Part-Time Worker	Non-Worker	Retired
(Intercept): M	2.11 ***	1.49 ***		
(Intercept): NM	1.13 ***	-0.04	0.59 ***	-1.17
Wheelchair Use: M	-1.87 ***	-3.38 ***		
Wheelchair Use: NM	-0.63	-1.90 ***	-0.72 ***	-1.26 ***
Works at home: M	-1.57 ***	-1.38 ***		
Works at home: NM	-0.07	0.1		
Male: M	-0.01	-0.05		
Male: NM	-0.16 *	-0.24 *	-0.28 ***	0.24 ***
Bachelor degree: M	0.38 ***	0.27 *		
Bachelor degree: NM	0.68 ***	0.53 ***	0.48 ***	0.35 ***
Income $25k - $50k: M	-0.09	0.01		
Income $25k - $50k: NM	-0.38 *	0.28	-0.06	-0.09
Income $50k - $100k: M	-0.23	-0.38 *		
Income $50k - $100k: NM	-0.34 *	-0.01	-0.06	0.11
Income > 100,000: M	-0.27	-0.40 *		
Income > 100,000: NM	-0.27	-0.06	-0.04	0.04
Age 40-64: M	0.02	0.54 ***		
Age 40-64: NM	0.06	0.97 ***	0.42 ***	2.24 **
Age 64-79: M	0.2	0.23		
Age 64-79: NM	0.83 ***	0.58 ***	1.67 **	2.13 **
Age 80+: M	22.96	2.07 *		
Age 80+: NM	22.63	2.16 *	14.56	1.54 *
Auto: M		0.41 **		
Auto: NM		0.75 ***		
ρ_C^2	0.03	0.06	0.02	0.03
AIC	26609.87	7418.73	4623.53	10689.72
Log Likelihood	-13282.94	-3685.37	-2301.76	-5334.86
Num. obs.	15936	4229	3764	9482

****p<0.001, **p<0.01, and *p<0.05*. M *represents "mandatory" DAP and NM represents "non-mandatory" DAP.*

4.4 Configuring ActivitySim for Wheelchair Users

The findings from the NHTS analysis show how wheelchair users behave differently in their daily travel patterns, and the DAP choice utility coefficients can be directly applied to ActivitySim to create specific plans for a synthetic population. The construction of the synthetic population will be described further in this section.

It is worth mentioning at this stage in the report that ActivitySim uses a coordinated plans model, or coordinated daily activity pattern (CDAP). This element of the ActivitySim model goes beyond the individual's DAP choice and models a coordinated activity pattern choice based on the daily activities of household members. The CDAP model will prioritize each member of a household and store the coefficients. Then depending on the DAP choices of each member, the model iterates new coefficients for each household member. For example, if a child is a pre-school age child, one parent will have a higher coefficient to stay home in the next iteration. Similarly, it is reasonable to expect that sharing a household with a wheelchair user might influence the choice of activity pattern for other household members. This influence could work in either direction: Another household member could conduct fewer out-of-home social activities; they might also conduct more maintenance or escorting activities to support a wheelchair-using household member. For this reason, both individuals who use a wheelchair and their household members may change their DAP when the wheelchair coefficient is considered in the DAP model.

To configure ActivitySim to account for wheelchair users and their household members in a coordinated effort and to understand their change in travel behavior, we designed a comparison between a base scenario ("Before") – where wheelchair use status is irrelevant – and a wheelchair test scenario ("After") where wheelchair users make DAP choices based on the wheelchair use coefficients found in Table 4-2 and repeated for convenience in Table 4-3. These coefficients are applied to the CDAP model in ActivitySim and rely on a condition of wheelchair status and person type, which can be found as person attributes in the synthetic population. With both scenarios, each person's behavior can be evaluated to see if wheelchair use has any effect on one's DAP; these results are discussed below.

Table 4-3 ActivitySim DAP Choice Coefficients

Person Condition	Mandatory	Non-Mandatory	Home
Full-time worker and uses wheelchair	-1.87	-0.63	0
Part-time worker and uses wheelchair	-3.38	-1.86	0
Non-worker and uses wheelchair	-	-0.72	0
Retired and uses wheelchair	-	-1.24	0

For ActivitySim to understand which individuals use wheelchairs, it was necessary to include a wheelchair use variable in the synthetic population. The synthetic population uses ACS PUMS data as a seed table, as described in Chapter 3; this table contains a "disability" variable, but not a specific wheelchair use variable. Disability, in this case, accounts specifically for ambulatory disabilities. Differently from the ACS, the NHTS data contains a "travel limiting" disability variable and specifies which, if any, medical devices are used (i.e., wheelchairs). Using the NHTS data, it is clear that 17.6 percent of those with a disability used a wheelchair. Using NHTS data, we estimated a binary logit regression model where the latent probability for wheelchair use is defined in Equation 3.

$$Wheelchair = -2.59 + 0.014 * age \tag{3}$$

The regression model enabled us to assign a probability of using a wheelchair for each person in the synthetic population, and then randomly identify synthetic individuals who use a wheelchair. Of the total synthetic population, those using a wheelchair consisted of 0.8 percent of the total population and had an appropriate distribution of age, accurate to the NHTS analysis.

Table 4-4 shows a summary of the population of wheelchair users from the NHTS data, and Table 4-5 displays a summary of the population of wheelchair users from the synthetic population. We see that ActivitySim will slightly overrepresent wheelchair users in "Full-Time Workers" and "Non-Workers" and largely underrepresent them in the "Retired" person type. Note that while the NHTS considers national distribution, the synthetic population only represents the Salt Lake City metropolitan area and such differences should be noted. The age variable is included to show that the average age within each person type is consistent with the NHTS data.

Table 4-4 NHTS Wheelchair User Population Summary

Person Type	Count	Average Age	Percent
Full-Time Worker	27	52.0	4.7
Non-Worker	112	50.7	19.5
Part-Time Worker	18	58.4	3.1
Retired	411	75.6	71.7
Driving Age Student	3	16.3	0.5
Non-Driving Student	2	14.0	0.3

Table 4-5 Synthetic Wheelchair Population Summary

Person Type	Count	Average Age	Percent
Full-Time Worker	2,039	52.9	9.9
Non-Worker	6,551	51.6	31.8
Part-Time Worker	987	54.2	4.8
Retired	10,070	79.0	48.9
Driving Age Student	47	16.6	0.2
Non-Driving Student	206	11.2	1.0
University	631	46.3	3.1
Pre School	67	5	0.3

4.5 DAP Analysis

The primary focus of the research at this stage is to measure the impact of wheelchair status on ActivitySim's selection of daily plans for our given synthetic population. Given a "Before" scenario in ActivitySim of the Salt Lake Area and ignoring the newly added wheelchair status in the synthetic population, ActivitySim predicted a DAP for each individual. In a second, "After" scenario, ActivitySim again predicted a DAP for each person, this time considering the wheelchair use status of each individual in the population. We hypothesized that those with wheelchairs and those in the same households as individuals with wheelchairs would change their DAP because of the negative utility scores applied to the "mandatory" and "non-mandatory" DAP alternatives, and the rest of the population would be unaffected. The DAP of those within the same household of a wheelchair user may change because of the coordinated nature of household DAP in ActivitySim. Table 4-6 shows the change in DAP among those with wheelchairs, in the same household as one with a wheelchair, and with neither a wheelchair nor in the same household. The table contains both total volumes and percentages; the value of percent is by total volume in the group, for example, 16.4 percent of Wheelchair Users chose a "home" pattern in both the "Before" scenario and in the "After" scenario. The latter group is rightly unaffected by the wheelchair implementation in the simulation (with the exception of a few changes attributable to randomness) and does not include a percentage breakdown. Primarily, DAP remain the same for most individuals, as shown in the diagonal. However, there is a large volume of wheelchair users and their household members that stay home, particularly from "non-mandatory" DAP. This finding is consistent with our hypothesis. A more detailed discussion of each group is included in sections 4.5.1 and 4.5.2.

Table 4-6 Comparison of DAP Before and After

Persons	**DAP Before**	**DAP After**		
		H	M	N
Wheelchair Users	H	3,369 (16.4%)	20 (0.1%)	459 (2.2%)
	M	932 (4.5%)	1,642 (8.0%)	308 (1.5%)
	NM	3,584 (17.4%)	23 (0.1%)	10,261 (49.8%)
Household Members	H	4,511 (12.3%)	213(0.6%)	631 (1.7%)
	M	759 (2.1%)	15,409 (42.1%)	301 (0.8%)
	NM	1,235 (3.4%)	415 (1.1%)	13,119 (35.9%)
Not Affected	H	309,965 (12.8%)	2 (0.0%)	0 (0.0%)
	M	2 (0.0%)	1,460,582 (60.1%)	0 (0.0%)
	NM	0 (0.0%)	2 (0.0%)	659,258 (27.1%)

The analysis of DAP comparison will focus on only the two groups: wheelchair users and their household members. Within each of these sections, there are those that did change their DAP and those that did not change. The analysis aims to further uncover the choices of each group. A summary of these groups is shown in Table 4-7.

Table 4-7 Analysis Group Description and Summary

Description	Total
Wheelchair user who changes DAP	5,326
Wheelchair user who does not change DAP	15,272
Household member who changes DAP	3,554
Household member who does not change DAP	33,039

4.5.1 Wheelchair Users

Of the 20,598 persons in the scenario who use a wheelchair, there is a notable shift toward a “home” DAP and away from “non-mandatory” DAP, as shown in Table 4-6 and Figure 4-1. Unfortunately, it is impossible to validate the volume of such a shift of wheelchair users in DAP, but the shift is consistent with the change to the utility coefficient. The primary metric of concern is the percent of wheelchair users that changes their DAP; Table 4-6 shows that 21.9 percent (4.5 percent + 17.4 percent) of wheelchair users that did not have a “home” DAP change to a “home” pattern. We notice that 74.2 percent (16.4 percent “home” + 8.0 percent “mandatory” + 49.8 percent “non-mandatory”) of all wheelchair users did not change their DAP, and 49.8 percent of all wheelchair users kept their “non-mandatory” DAP. We also see that 38.3 percent (16.4 percent “home” + 4.5 percent “mandatory” + 17.4 percent “non-mandatory”) of all wheelchair users selected a “home” DAP in contrast to the 18.7 percent (16.4 percent + 0.1 percent + 2.2 percent) that selected “home” DAP before they were assigned a wheelchair.

Figure 4-1 shows the choice of DAP for individuals who change their DAP in the wheelchair test scenario. The left-hand histogram shows their DAP choice before any wheelchair choice coefficients were applied to ActivitySim, and the right-hand histogram shows their DAP choice after the choice coefficients were applied. There is an obvious trend of “home” DAP selected by individuals who change, and the volume increases with age. This is clear evidence that wheelchair use has an effect on DAP, according to our model.

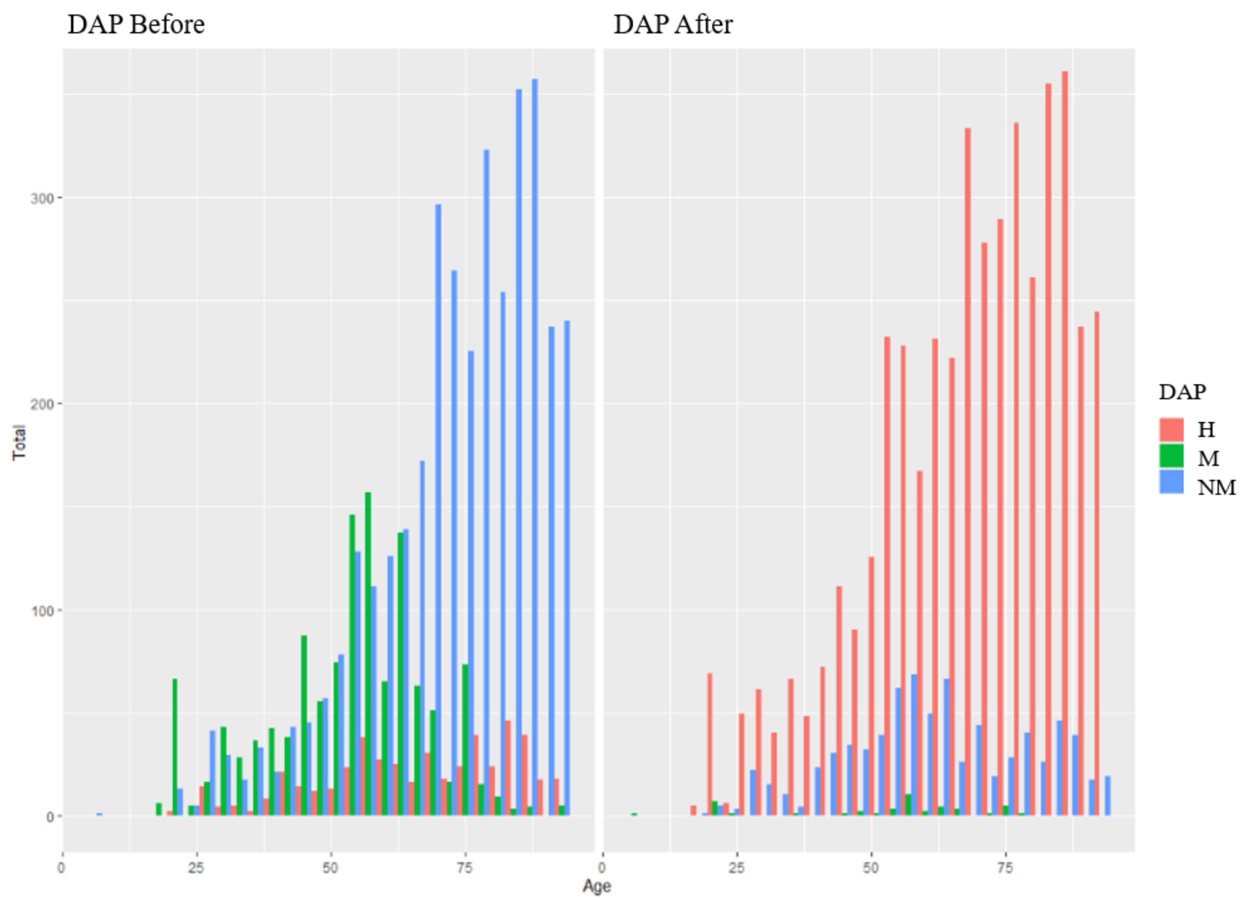

Figure 4-1 Histogram of wheelchair users who change DAP.

4.5.2 Household Members

The research also investigates the changes of those living in the same household as wheelchair users, as ActivitySim models a coordinated choice pattern at the household level. For the most part, household members maintain their original DAP, as shown in Table 4-6; those who did consist of 90.3 percent (12.3 percent "home" + 42.1 percent "mandatory" + 35.9 percent "non-mandatory") of the household members. The volume of household members that changed their DAP to a "home" DAP was 5.5 percent (2.1 percent "mandatory" + 3.4 percent "non-mandatory"). These results show that the use of a wheelchair has an effect on household members, although the effect is relatively small.

4.6 Summary

Existing literature has shown a variance in conclusions in explaining mobility for individuals with disabilities and is limited in representing a quantitative analysis of how wheelchair use affects one's choice of activities. An objective of this research and the goal of this chapter is to understand the effect of wheelchair use on one's choice of DAP. This evaluation consisted of a study of wheelchair users in the 2017 NHTS and an analysis of their daily activity patterns, an estimation model and the derivation of DAP choice coefficients, the implementation of these coefficients into the ActivitySim model, and an analysis of their change in DAP when compared to the base scenario.

In considering the analysis of the DAP of individuals from the 2017 NHTS, the results from the estimation model analysis showed that using a wheelchair decreases (through a negative utility coefficient) the likelihood of an individual to choose a "non-mandatory" DAP and even more strongly the likelihood of choosing a "mandatory" DAP. Implementing these utility coefficients into ActivitySim, the findings show many wheelchair users chose to stay home, and consequently some of their household members also chose not to leave the home. We noticed that more wheelchair users stayed home if their base scenario DAP was "non-mandatory" rather than "mandatory." An important note is that the change in DAP, at this stage, is not reflected by a potentially better transportation service. In other words, users may be more likely to choose a different daily plan if transportation were more accessible, and this is neither represented in our estimation model nor ActivitySim simulation.

While the findings of this chapter are significant, there are some limitations worth mentioning. The NHTS is a fundamental data set for examining travel behavior of individuals across the United States, but it does have several known limitations. The sampling strategy, though improved from previous versions of the NHTS, does not adequately capture the travel behavior of young adults and university students (Xueming, 2012). For this reason, these person types were excluded from the analysis of DAP. Wheelchair use is perhaps not as common among young adults as it is among the aging and elderly, but younger adults are perhaps more likely to take advantage of the *mobility-as-a-service* systems that motivate this study. This project also used the NHTS across the whole country instead of accounting for geographical differences (though we did filter out respondents not residing in medium-large urban areas). This was decided as to accumulate enough respondents who use wheelchairs to actually estimate the models. Finally, the NHTS is also a self-reported survey with no supplemental data elements. Modern household travel surveys typically include some elements that are collected passively through smartphone applications or GPS devices; these additional methods provide assurance that the daily patterns reported in the survey are valid and complete.

On the foundation of Figure 1-1, this chapter provided the context of understanding the effect of wheelchair use on DAP output from ActivitySim and provides the framework to apply those DAP to the BEAM simulation.

CHAPTER 5 SIMULATION OF WHEELCHAIR-ACCESSIBLE VEHICLES

5.1 Overview

This chapter aims to apply the findings of Chapter 4 to model a WAV system. With the understanding of such behavior reported in the previous chapter, the findings in this chapter add a layer of application by seeking to understand the performance of WAVs in a microsimulation of these wheelchair users and their households using BEAM. BEAM was primarily selected for its ability to update the mode choice of each individual over multiple iterations based on the modes and travel times available to each person. An activity-based model uses average travel times by period and mode to evaluate mode choices. In the case of small, on-demand transportation offerings like a WAV system, these average times are highly variable and unrealistic: The amount of time spent waiting for an on-demand vehicle is highly dependent on demand for that vehicle in other parts of the region. A microsimulation can help to determine travel times and vehicle availability in a more realistic way. This chapter describes the implementation of the WAV simulation scenarios in the BEAM agent-based modeling software, focusing on the performance of the vehicles.

BEAM stands for Behavior, Energy, Autonomy, and Mobility and is an agent-based microsimulation model developed at Lawrence Berkeley National Laboratory and the UC Berkeley Institute for Transportation Studies. BEAM extends the MATSim modeling framework by improving the performance of the multi-agent simulation on large networks as well as standardizing several features that are add-ons in standard MATSim. In this research, BEAM was selected for its integrated ride-hail algorithms, as the focus of this project is to evaluate the performance of WAVs in an on-demand, ride-hail environment.

This chapter first describes the input structure of BEAM including the population activity plans, transportation services, and the BEAM simulation code. After a discussion on data inputs for BEAM, this chapter includes an analysis of the WAV simulation including the construction and results of the scenarios. The scenarios are prepared to evaluate the performance of the WAVs in the Salt Lake area by measuring the average wait time for wheelchair users and the general utilization statistics of these vehicles. This chapter concludes with the summary of this performance analysis.

5.2 Inputs to BEAM

A BEAM scenario includes three distinct elements that function together:

- Daily activity patterns developed from ActivitySim outputs
- Transportation services including highway infrastructure and transit, and taxi / ride-hailing services
- BEAM simulation code and scenario construction

These elements are discussed in the following sections.

5.2.1 Population Activity Plans

As the primary input into BEAM, a population activity plans file consists of each activity to which an agent will travel during the day and their chosen mode of transport to each activity. BEAM simulates these plans, and then updates the plans using adaptive algorithms that perturb the initially chosen routes, departure times, and mode choices to optimize their overall utility. This innovative selection of mode choice is why BEAM was chosen as the simulation tool and provides insight into how people might choose novel transportation modes. However, while BEAM innovates the mode choice, the selection of activities remains constant. These population activity plans are generated from ActivitySim's output.

As part of ActivitySim's output, a trips file is generated. This file contains an origin TAZ and a destination TAZ, a departure hour, a trip purpose, and a travel mode for each trip. While all this information is useful, it has two main issues: First, the organization of trips is not recognized by BEAM, as BEAM reads activities; second, the data lacks specific coordinates representing facilities and households. For these reasons, we converted the ActivitySim output into BEAM input by creating activities from the trips and randomly selecting specific coordinates within each origin and destination TAZ for facilities and homes.

The selection of random coordinates for both facilities and homes was necessary for BEAM to simulate agents' plans. Coordinate information comes from the AGRC. Household coordinate information is assigned by number of households within a TAZ and then randomly scattered within the given TAZ. Using a similar randomization technique and information from AGRC, we also assigned coordinates to each facility in the simulation. These coordinate tables, for both households and facilities, were used to randomly assign coordinates that belonged within TAZ from the ActivitySim trips file.

5.2.2 Transportation Services

BEAM requires a description of the transportation services available for the agents to use when traveling between activities. The infrastructure includes a highway network, a transit schedule, and a unique taxi specification—where individuals with wheelchairs are excluded from inaccessible taxis.

A highway network in BEAM consists of nodes where activities occur, connected by links. The links on the network need to be composed of attributes relating to capacity, free flow speed, functional classification, drivetime, and direction, whether it is a one-way street or not, etc. These attributes allow the model to simulate more accurately the real-life road environment of the Salt Lake Area.

A detailed road network for the state of Utah was obtained from OpenStreetMap via the GEOFABRIK download service (OpenStreetMap, 2020) and manipulated using the Osmosis command-line tool (Osmosis, 2021). The area of interest was then extracted from this file using a bounding box from North Ogden to Santaquin as shown in Figure 5-1, and the road-related streets were then filtered using Osmosis, so that only certain highway links remained. A depiction of the final roadway network focused on Salt Lake County is given in Figure 5-2.

A common format for public transportation schedules and geographic information is the General Transit Feed Specification (GTFS). This format allows public agencies to publish their data in a format digestible by many software packages. We obtained GTFS data representing UTA as of April 2019 from the open mobility data feed (UTA, 2021). BEAM maps the GTFS data onto the OSM-based highway network, allowing simulated agents to use highway and transit services interchangeably.

BEAM already has an advanced infrastructure for simulating on-demand ride-hail vehicles. However, it lacks the functionality of wheelchair accessibility. As part of developing the infrastructure for BEAM to simulate WAVs on demand for a population of wheelchair users, it was necessary to extend BEAM to recognize both WAVs and wheelchair users.

The first step in creating WAVs with all-inclusive functionalities was to define WAV as a new vehicle type in BEAM and add a new "accessibility" attribute to the vehicles in the ride-hail fleet. In addition to defining WAVs and their distinction from ride-hail vehicles, it was necessary to specify wheelchair users and their distinction from the general population. As such, wheelchair users were given a wheelchair status attribute and their user identifications included a "wc" in the string ID. Using a string instead of a person's attribute proved more efficient to highlight wheelchair users in filtering their ride-hail requests.

With both wheelchair users and WAVs identifiable in BEAM, we implemented a filtering method that excluded wheelchair users from general ride-hail cars, as they are inaccessible to wheelchair users. The WAVs on the other hand were accessible to both wheelchair users and the general population. To allocate users to vehicles, BEAM uses a vehicle centric matching algorithm and a pooling algorithm to assign requests to available (and now accessible) vehicles nearby and heading in similar directions as the request. BEAM also uses a default pooling that is request centric and assigns a request to a vehicle if the first assignment failed. To successfully exclude wheelchair users from all inaccessible ride-hail vehicles, it was necessary to write logic in both methods: the vehicle centric and pooling classes and the request-centric backup pooling class.

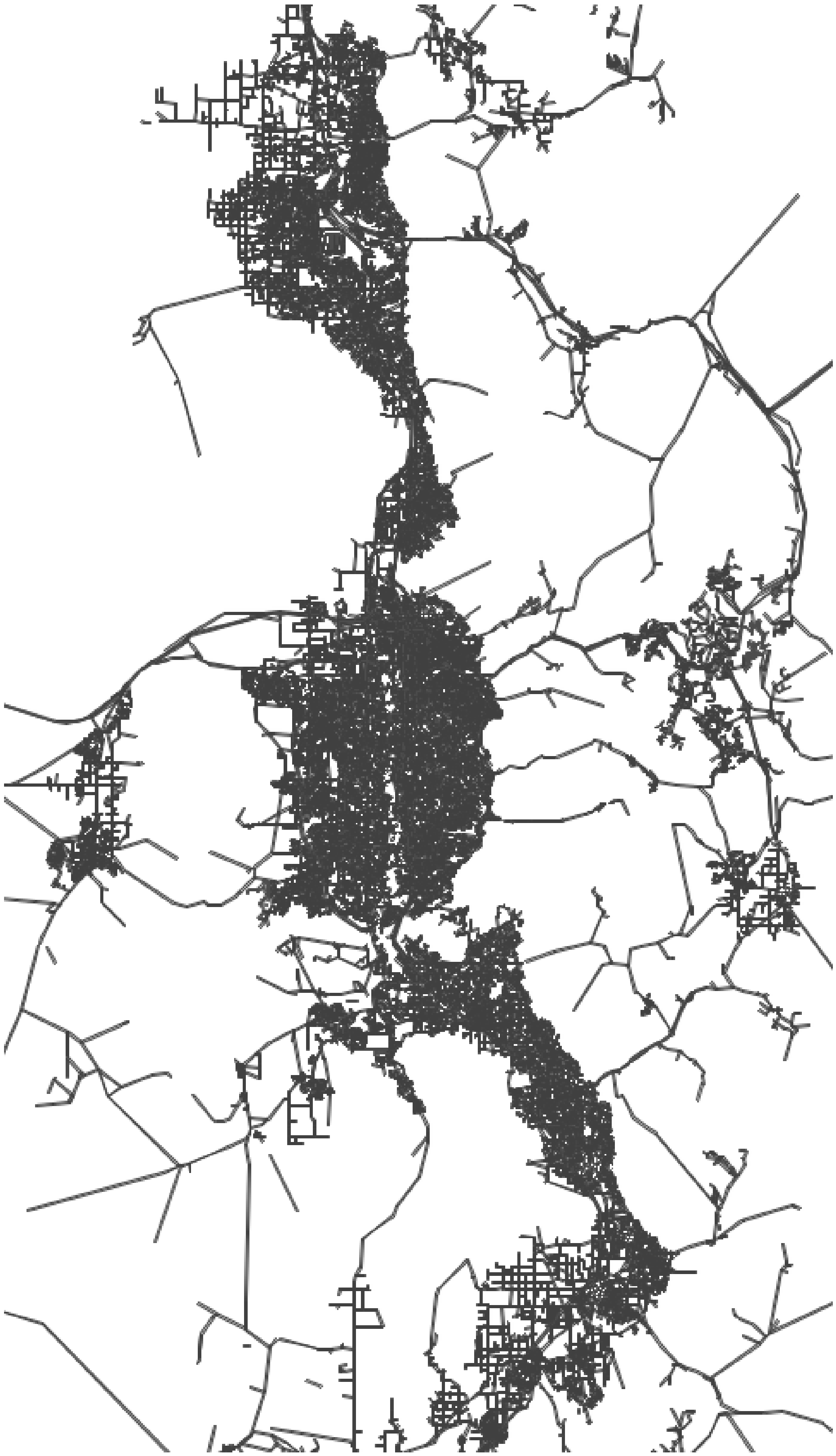

Figure 5-1 Road network of the Greater Salt Lake Area.

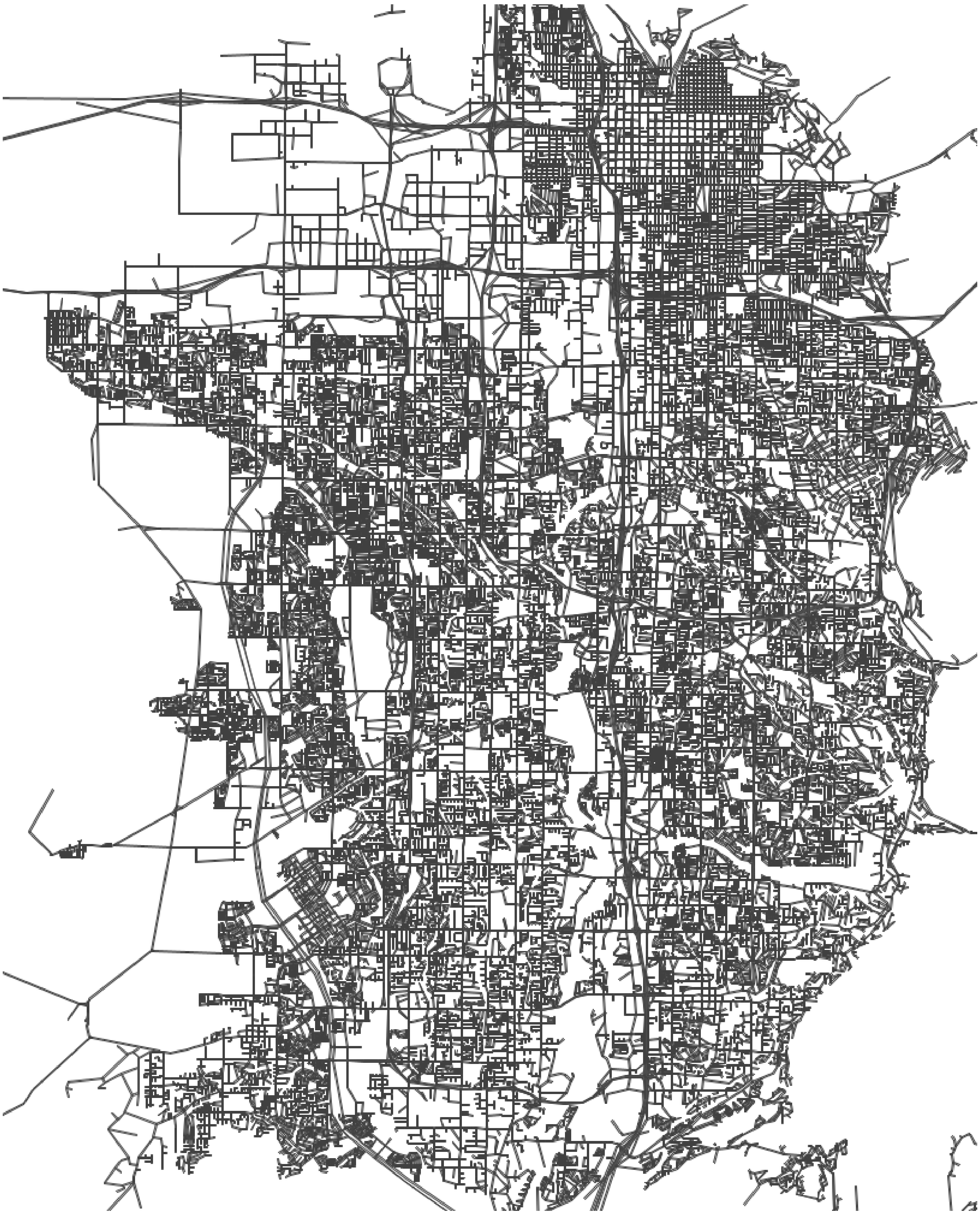

Figure 5-2 Road network of Salt Lake county; zoomed in for detail.

5.2.3 BEAM Simulation Code

This section will highlight the changes and improvements to create a BEAM scenario with the previously mentioned input data including validation and calibration, mode choice innovation, and ride-hail fleet information.

The BEAM simulation in the Salt Lake Scenario is calibrated to the accuracy of the population activity plans, as described in Section 5.2.1. At this level of calibration, the modal split from BEAM reflects the modal split from ActivitySim, which calibration was described in Section 3.3. As the secondary contribution of this research is to evaluate the performance of WAVs, the modal split from ActivitySim is acceptable, and mode innovation is only available to wheelchair users.

Mode innovation is the process that BEAM runs to optimize the mode selected by agents over the multiple iterations in a scenario. With mode innovation turned off for the general population, each of the agents are forced to stay with their original mode selection, given by the input population activity plans file. However, as the population of wheelchair users and their mode choice behavior are to be evaluated, mode innovation remained “on” for the wheelchair user population only, and only 20.0 percent of the population would reevaluate their mode selection between iterations. This strategy allows for some wheelchair users to select a different mode if they, for example, spent too much time waiting for a WAV in a previous iteration.

The ride-hail fleet is another input file into BEAM and is a critical component of each scenario in this analysis. The ride-hail fleet component contains a unique ID for each vehicle and a starting location. The starting location was determined by randomly selecting coordinates of nodes in the network and converting the coordinates to the appropriate coordinate system. The ride-hail fleet size was a function of the population size and was calculated according to the ratios reported by Castiglione et al. (2017), and using the proportions given, a “ride-hail vehicle by population” ratio was back calculated. There are roughly 21,000 TNC drivers in San Francisco (population 874,926). This means that there is roughly 2.3 percent of a population that serves as a driver. As ride-hail volume in general is lower in Salt Lake City compared to San Francisco, and for lack of a deeper understanding of the nature of ride-hailing volume in Salt Lake City, a value of 2.0 percent was used in calculating ride-hail fleet size.

5.3 Analysis of WAV Simulation

As has been described, the goal of these experiments is to compare how *wait times* and *frequency of use* change as more WAVs are introduced into the scenarios. While future research can provide information as to the optimal fleet size for WAV systems, this analysis is not sufficiently calibrated to model mode choice of the Salt Lake Area. Thus, this section will discuss the construction of the "WAV" scenarios used to evaluate the performance of WAVs in the Salt Lake area. This section will also describe how wait time and frequency of use change as more WAVs are introduced into the scenario.

5.3.1 Scenario Construction

In this research there are two scenarios that were tested to evaluate the performance of WAVs. These scenarios will then be run four times each (a total of eight simulations) with a different number of WAVs: 4, 8, 16, and 32, each time simply taken from the input ride-hail fleet size (i.e., if the fleet size is 1000, then 32 are WAVs and 968 are general ride-hail vehicles). Then wait times and usage statistics were compared among the varying runs of each scenario. The two scenarios are structured as follows:

1. All wheelchair users and their households, roughly 2.5 percent of the population – From the synthetic population, there are 20,518 wheelchair users in the Salt Lake Area. This scenario includes each wheelchair user and everyone from their households. The total population of this scenario is 57,273 from 20,110 households. The total number of ride-hail vehicles for this scenario is 1,000 (general vehicles plus WAVs) and the wheelchair users represent 36.0 percent of the scenario population (20,598 wheelchair users).
2. Roughly 5.0 percent of the total population, including all of scenario 1 – Of the 20,110 households of wheelchair users, we randomly selected 20,000 more households (excluding 486 randomly selected, duplicate wheelchair users' households) for a total of 39,624 households, a population of 115,346, and 2,500 ride-hail vehicles (general vehicles plus WAVs). The wheelchair users represent 17.9 percent of the scenario population (20,598 wheelchair users).

The strategy of selecting the two scenarios in this way was to optimize run time and still have a sufficient number of wheelchair users in each scenario. While in both scenarios there is an incorrect proportion of wheelchair users to the true population, only the individuals with wheelchairs are allowed to change their choice of mode within the simulation; the general population does not alter their mode choice between iterations. This way the demand for WAVs should remain mostly unaffected by the increase in general population size. Scenario 2 is designed to be twice the size of scenario 1 in an effort to see how volumes and wait times would change when a larger population is tested and the number of wheelchair users remains constant. The purpose of processing multiple runs of each scenario with a larger WAV fleet size is to evaluate how wait time changes as more WAVs are introduced into the scenarios. The analysis of these runs is explained in the following section.

5.3.2 Scenario Analysis

For each scenario, the metrics of analysis include the wait time for WAVs—this refers to the average time that wheelchair users spend waiting after their request, the number of WAV requests from wheelchair users, the proportion of WAV requests to WAV fleet size, the number of wheelchair users that ride in a WAV, the total number of rides in a WAV, the wait time for general ride-hail cars, and the total number of rides in general ride-hail cars. The results are found in Table 5-1 for Scenario 1 and Table 5-2 for Scenario 2.

The central finding from these scenarios is the demand increases as WAV fleet size increases. The results in both Table 5-1 and Table 5-2 show that as more WAVs are introduced, the demand increases linearly; they also show that wait time for wheelchair users remains nearly constant across both scenarios. This indicates some kind of relationship among the supply of WAVs, the demand of wheelchair users, and the wait time. One hypothesis here is that BEAM does not tolerate a wait time above a certain threshold. This would force agents to choose to walk or drive instead, but to validate this assumption of wait-time threshold, further research is required.

The other possible explanation for this fixed wait time is that these simulations did not simulate through enough iterations. Over various iterations, agents will reselect their mode to optimize their utility over the day. The mode choice in each iteration for Scenario 1 with 32

WAVs is shown in Figure 5-3; this image adequately reflects the mode choice plots from the other scenarios, differing only in "# of mode chosen." Notice that the only modes that seem to change are "car" and "walk," and ride-hail modes seem to maintain constant volume.

The analysis of WAV performance from these two scenarios gives insight into the inner workings of BEAM and sets a strong foundation for future research in microsimulation of micromobility. While these results are informative, they are not final for the purpose of advising on optimal fleet size or estimating wait times; further research is required.

Table 5-1 Wait Time and WAV Usage Statistics – Scenario 1

Metric	**Number of WAVs**			
	4	8	16	32
Average WAV Wait Time	8.1 min	9.3 min	8.3 min	8.3 min
Number of WAV Requests	19	52	77	209
Average Number of Request per WAV	4.8	6.5	4.8	6.5
Number of WC Rides in WAV	13	34	63	178
Number of Total Rides in WAV	14	36	64	188
Average General Ride-Hail Wait Time	5.2 min	5.1 min	5.2 min	5.1 min
Total General Ride-Hail Rides	3,145	3,162	3,139	3,199

Table 5-2 Wait Time and WAV Usage Statistics – Scenario 2

Metric	**Number of WAVs**			
	4	8	16	32
Average WAV Wait Time	7.6 min	7.1 min	7.8 min	7.7 min
Number of WAV Requests	31	43	84	146
Average Number of Request per WAV	7.8	5.3	5.3	4.5
Number of WC Rides in WAV	18	28	61	115
Number of Total Rides in WAV	20	31	64	124
Average General Ride-Hail Wait Time	10.1 min	11.4 min	10.8 min	10.2 min
Total General Ride-Hail Rides	2,646	3,101	2,669	2,579

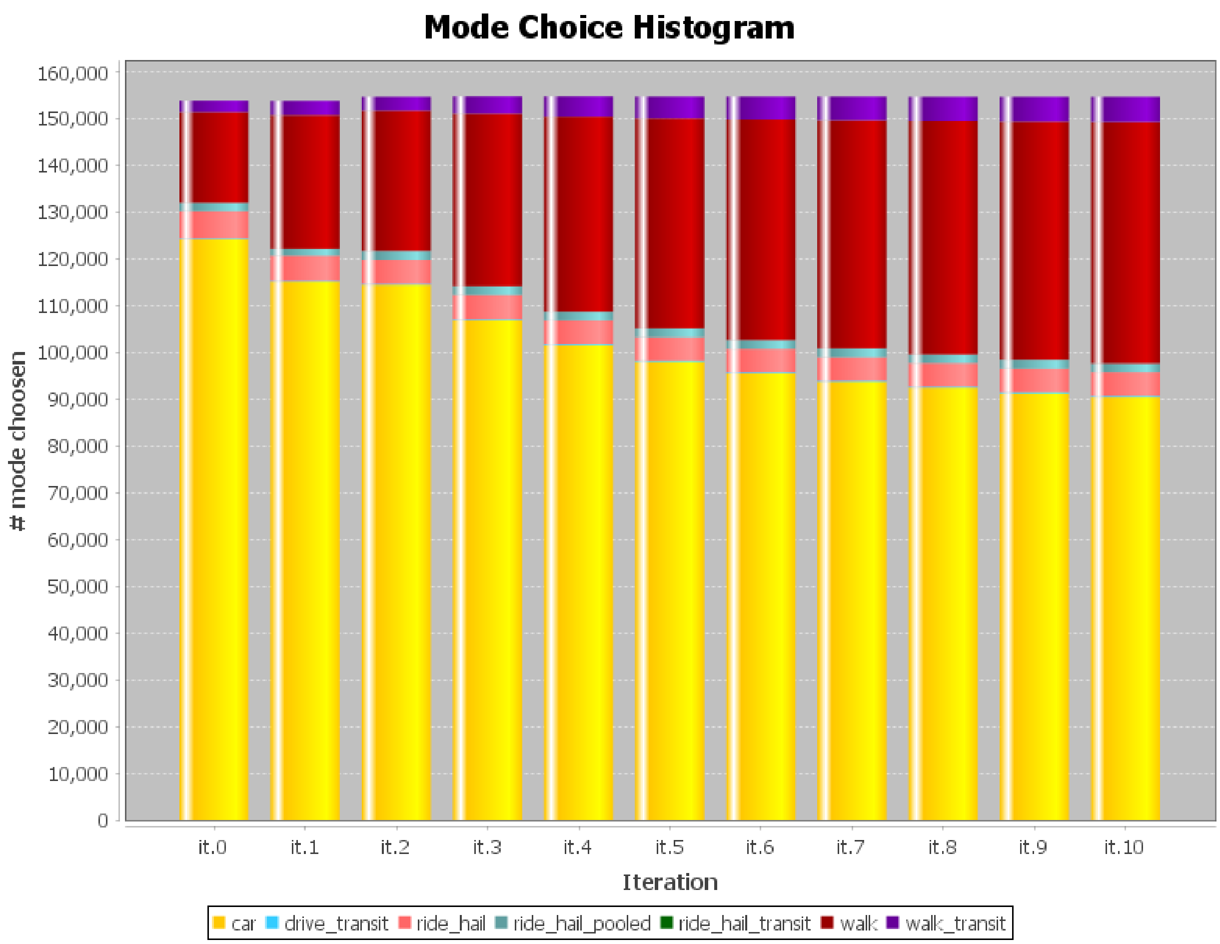

Figure 5-3 Mode choice over iterations from Scenario 1 with 32 WAVs.

5.4 Summary

With conclusive findings from Chapter 4 on the behavior of individuals with wheelchairs, this chapter models a WAV system, highlighting the evaluation of vehicle performance in a microsimulation of WAVs in BEAM. The microsimulation tool BEAM was used for its comprehensive algorithms in simulating ride-hail and pooling scenarios.

To implement BEAM to simulate WAVs effectively in Salt Lake City, some manual restructuring was required. Referring to Figure 1-1, BEAM simulates the activity plans, DAP, of a population including the addition of wheelchair users, and these plans came from the output of ActivitySim. BEAM also required the adaptation of a new transportation network and system to properly simulate the Salt Lake Area. Lastly, we configured BEAM to recognize both wheelchair users and WAVs and allocate them accordingly.

After simulating two scenarios of different wheelchair saturation levels, the findings show that request volume from wheelchair users increases linearly with the increase of WAV fleet size. We were surprised that with increased demand, the wait time for WAVs remained constant. This could be due to an insufficient number of iterations or to a threshold within BEAM of agents' willingness to wait.

BEAM is a powerful microsimulation tool with a rigorous infrastructure for modeling ride-hail scenarios. However, there are some limitations; for example, BEAM restricts the activity choice of all agents to the activities assigned in the input file. Ideally, in a system that improved mobility for a population of individuals with wheelchairs, their activity patterns would change. Despite the limitations, these efforts show an application of the behavior of individuals with wheelchairs in a WAV scenario. The findings also give further insight into BEAM concerning the relationship among the supply of ride-hail vehicles, demand, and wait time.

CHAPTER 6 CONCLUSIONS

6.1 Contributions

Individuals with mobility limitations are an important part of the transportation system, though they are often given secondary consideration, if any, from planners and service providers. Existing literature has come to a variety of conclusions in considering the travel behavior, mode choice, trip frequency, and activity patterns of individuals with disabilities. The need to further understand and quantify their travel patterns grows as modern mobility services become more common such as ride hailing, on-demand microtransit, and other services, which are often inaccessible or highly inconvenient to individuals with wheelchairs. The literature also showed efforts made by public and private organizations to improve transportation for those with wheelchairs, and this research provided quantitative evidence to explain the travel patterns of individuals with wheelchairs.

Motivated by the 2018 efforts of UTA to launch a wheelchair-accessible ride-hail service, this report made two primary contributions to the existing research surrounding mobility for individuals with disabilities and the simulation of micromobility scenarios. First, this report demonstrated understanding of the effect of wheelchair use on one’s choice of DAP. Consequently, the report presented a thorough analysis of the travel behavior of individuals with wheelchairs from the 2017 NHTS with the purpose of modeling their DAP and measuring the effect of wheelchair use on their daily patterns, as shown in the red shapes of Figure 6-1. Second, this research applied the understanding of DAP choice by modeling a WAV system. As such, this report analyzes the performance of on-demand WAVs in a microsimulation in BEAM by simulating the plans of wheelchair users from ActivitySim, as shown by the blue shapes in Figure 6-1.

Of the findings regarding the effect of wheelchair use on DAP choice, the analysis of the 2017 NHTS shows that there is a significant and negative utility for all person types who use a wheelchair. These negative utility coefficients are informative as to their travel patterns and are useful as input into the ActivitySim model. Two scenarios were run in ActivitySim as part of this research to compare the effect of wheelchair use against a base scenario. From the simulation of the synthetic population in ActivitySim, the findings were conclusive in that of the wheelchair users who changed their DAP according to the negative choice coefficients. The large majority chose a “home” daily activity pattern, primarily among the elderly. The analysis shows the significant effect of wheelchair use in one’s choice of DAP.

By understanding one’s DAP, this research applied this understanding of wheelchair users to model a WAV system. In this simulation, the performance of these vehicles was evaluated as more vehicles were introduced into the scenario. The findings are conclusive in that demand increases linearly with fleet size and can maintain higher demands under a wait-time threshold. This is informative as to understand on a deeper level how the BEAM simulation tool approaches ride hailing and lays a framework for further research in BEAM.

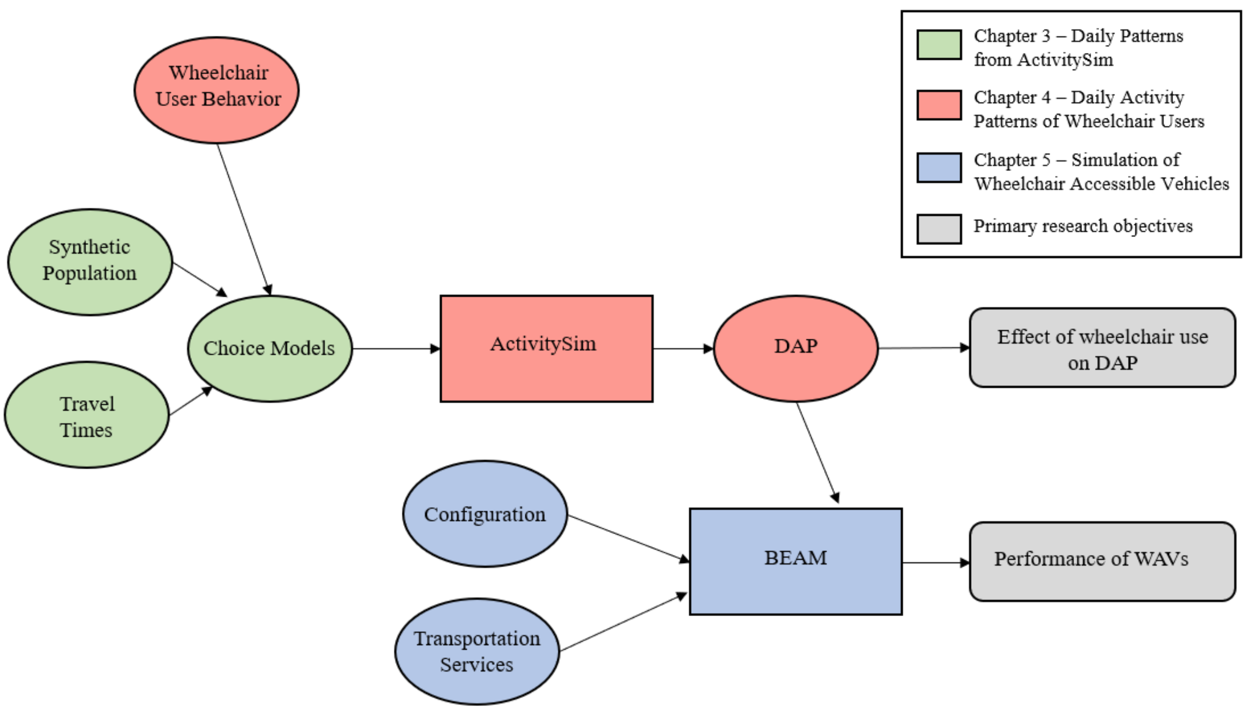

Figure 6-1 Overview of research and organization of report.

6.2 Recommendations

The contributions of this research provide adequate information on the effect of the use of wheelchairs on daily activity plans and on the performance of on-demand WAVs in Salt Lake City. In this process, these efforts produced a calibrated ActivitySim scenario of Salt Lake City and a working scenario of BEAM. These tools, with further calibration efforts, can be used to simulate modern and emerging micromobility scenarios in the Salt Lake area.

This study leaves a few questions for future study. For example, in another BEAM scenario of WAVs and wheelchair users, how might wait time change if demand is held constant? This study would require a deeper understanding of how BEAM manages the demand with the supply of ride-hail vehicles. A future study like this might benefit UTA in looking to optimize a potential fleet size.

One future step to improve the study of the behavior of individuals with wheelchairs concerns additional models within ActivitySim. The DAP model is only the first of many choice models in the ActivitySim framework. Subsequent choices include “mandatory” and discretionary location choices, tour and trip mode choices, and incidental activity generation. It is likely that wheelchair use influences all of these travel behaviors, but we could consider only the DAP choice in this research. Further exploration of the role that wheelchair use – and other disabilities – plays in travel behavior choices is essential to developing policies and services that will provide equitable mobility for this population.

ActivitySim was used in this research project because the current WFRC / MAG travel demand model was not sufficiently sensitive to the behavioral issues at play, and could not generate coherent daily activity patterns to simulate in BEAM. A fully-calibrated and specified activity-based model would have provided more realistic inputs to the microsimulation as well as simplified some of the scenario construction tasks described in Chapter 3.

Another future step of research revolves around the activity innovation within BEAM. In this study, activity selection was held constant as to only analyze mode shift. However, in reality when a new mode becomes available, one’s activities would also change. This research would require more simulation within the ActivitySim model to measure how activities change with new availability to accessible travel. Perhaps an iterative study from the mode change in BEAM to then inform ActivitySim's activity models would be necessary.

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APPENDIX A – THE SEGMENTATION MODEL ANALYSIS

ActivitySim classifies persons into seven segments, as mentioned in Chapter 4, however, only four of these person types are considered in the research. The analysis presented in this Appendix shows the consideration of a fifth person type: "wheelchair user." Using the results from the NHTS model, a principal question in responding to its accuracy is whether individuals who use wheelchairs are sufficiently distinct in their behavior to warrant independent segmentation. The estimation analysis mentioned in the report considers wheelchair use as a significant variable in the other person-type segments. By also considering wheelchair users as a segmented person type, we can evaluate the difference in accuracy between the two models: the model that considers wheelchair use as described in Section 4.3 and a model that considers wheelchair users as a segmented person type. Table A.1 shows the results from both models with the Wheelchair User on the far right representing the estimates from the segmented person-type model. The sign and magnitude of the coefficients are consistent with those of the existing person types where wheelchair is a variable.

To determine if the activity pattern choices of wheelchair users are sufficiently distinct to warrant a distinct population segment, we can compare the predictive accuracy of each model pair for all wheelchair users.

That is, each wheelchair user i in the estimation data set has two utility estimates: one for the person type segment U_{ik} from which the individual would belong, and one from a segmented wheelchair user person type U_{iWC}. The expected probability of this individual's chosen alternative plan j* is represented mathematically in Equation A-1.

$$P_{ij*} = \frac{e^{U_{ij*}}}{\sum_{j \in M,NM,H} e^{U_{ij}}} \tag{A-1}$$

A perfect model would give a probability of 1 to the chosen alternative and 0 to all other alternatives. While the estimates in Table A.1 are far from perfect, it is informative to consider the average difference in expected probabilities between the two models. After finding both utility estimates for all wheelchair users in the data set, the average difference would show if one model was preferred to the other. Equation A-2 shows the average difference in expected probabilities between the wheelchair user segment model P_{iWC} and the person-type segment model P_{ik} where wheelchair use is a variable in the model (N_k is the number of individuals in the relevant person segment).

$$\Delta_k = \frac{\sum_{i=1}^{N_k} P_{iWC} - P_{ik}}{N_k} \tag{A-2}$$

Given the direction of Equation A-2, a positive value for Δ_k indicates that the wheelchair segment model gives a higher expected probability than the applicable person segment model. The averages and standard deviations of these differences are shown in Table A.2 for all wheelchair users of each person type, as well as the results of a *t*-test where the null hypothesis states no difference between the two models. Overall, there is no significant difference between the two approaches.

Table A.1 Model Estimate Results

	Full-Time Worker	Part-Time Worker	Non-Worker	Retired	Wheelchair User
(Intercept): M	2.11 ***	1.49 ***			-2.40 *
(Intercept): NM	1.13 ***	-0.04	0.59 ***	-1.17	0.34
Wheelchair Use: M	-1.87 ***	-3.38 ***			
Wheelchair Use: NM	-0.63	-1.90 ***	-0.72 ***	-1.26 ***	
Works at home: M	-1.57 ***	-1.38 ***			-5.62 *
Works at home: NM	-0.07	0.1			2.36 **
Male: M	-0.01	-0.05			1.56
Male: NM	-0.16 *	-0.24 *	-0.28 ***	0.24 ***	0.45 *
Bachelor degree: M	0.38 ***	0.27 *			
Bachelor degree: NM	0.68 ***	0.53 ***	0.48 ***	0.35 ***	
Income $25k - $50k: M	-0.09	0.01			-0.17
Income $25k - $50k: NM	-0.38 *	0.28	-0.06	-0.09	-0.56 *
Income $50k - $100k: M	-0.23	-0.38 *			-2.44
Income $50k - $100k: NM	-0.34 *	-0.01	-0.06	0.11	-0.15
Income > 100,000: M	-0.27	-0.40 *			3.78 ***
Income > 100,000: NM	-0.27	-0.06	-0.04	0.04	-0.31
Age 40-64: M	0.02	0.54 ***			-4.16 **
Age 40-64: NM	0.06	0.97 ***	0.42 ***	2.24 **	-0.41
Age 64-79: M	0.2	0.23			-0.71
Age 64-79: NM	0.83 ***	0.58 ***	1.67 **	2.13 **	0.14
Age 80+: M	22.96	2.07 *			-15.45
Age 80+: NM	22.63	2.16 *	14.56	1.54 *	-0.4
Auto: M		0.41 **			
Auto: NM		0.75 ***			
Retired: M					-5.31 *
Retired: NM					-0.54 *
Fulltime Work: M					4.45 ***
Fulltime Work: NM					-1.32
Rho2	0.03	0.06	0.02	0.03	0.14
AIC	26609.87	7418.73	4623.53	10689.72	833.13
Log Likelihood	-13282.94	-3685.37	-2301.76	-5334.86	-394.57
Num. obs.	15936	4229	3764	9482	573

****$p<0.001$, **$p<0.01$, and *$p<0.05$. M represents "mandatory" DAP and NM represents "non-mandatory" DAP.*

Table A.2: Predictive Model Accuracy

Person Segment	*Count*	$\Delta_{\boldsymbol{k}}$	*Std. Deviation*	*t-statistic*	*p-value*
Full-time	27	0.1477	0.34	2.25	0.016
Part-time	18	0.0403	0.36	0.48	0.320
Non-worker	112	-0.0155	0.16	-1.05	0.148
Retired	411	-0.0068	0.10	-1.39	0.082
Total	568	0.0004	0.15	0.06	0.478

There is apparent variation in the models' predictive power at the person segment level. For individuals who use wheelchairs and work full-time, the wheelchair segment model on average gives an expected probability of the chosen alternative 0.148 higher than the full-time worker model controlling for wheelchair use (on a scale of 0 to 1). This result is significant at the 95.0 percent confidence level. For retired and non-working individuals who use wheelchairs, the respective segment models are only slightly more predictive of the chosen alternative, but the difference is not significant.

It is curious why the wheelchair segment model would be more accurate for full-time workers than for the other person types, when these individuals make up only about 5.0 percent of the population who use wheelchairs. One expectation would be that the wheelchair segment model would be least accurate for this group, as its estimated coefficients could be driven by the behavior of non-working and retired individuals. On the other hand, it is also reasonable to imagine that wheelchair users who are also full-time workers exhibit choice behavior that is more similar to other wheelchair users than to full-time workers who do not use wheelchairs. It is also possible that there is another missing variable or interaction of an existing variable with wheelchair status that would improve the predictive accuracy of the full-time worker segment model for wheelchair users.

To summarize, the activity pattern choice of wheelchair users who work full-time would be more accurately represented with an additional person-type segment including all wheelchair users. The choices of wheelchair users in other person-type segments, by contrast, are not more accurately predicted by the standard person-type segmentation when including wheelchair status as a variable in the choice utility function. There may even be some suggestive evidence that a distinct wheelchair user segment is less predictive of the choices in some segments. With this evidence, it is reasonable to maintain the existing person-type segmentation in the analysis of DAP in ActivitySim, but to add a variable that adjusts the utility of choosing a DAP if the individual uses a wheelchair.