T-SCORE

Transit Serving Communities Optimally, Responsively, and Efficiently Center

Final Report - Project M4

January 2023

Implementation and Quantitative Evaluation

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16. Abstract

The T-SCORE research team developed a Multi-Modal Optimization and Simulation (MMOS) framework to capture the interactions between travelers, transit systems, and private mobility providers. The MMOS combines three layers, each representing a different type of actor. The central layer represents travelers who aim to maximize their own utility. It includes two modeling components: an activity-based model of travel demand generates the daily travel plans for a synthetic population of a city, and a multi-agent simulation predicts how those agents move through a multi-modal network and the congestion impacts as they do so. The bottom layer represents behavior of private mobility providers, such as ride-hailing drivers, that aim to maximize their own profit. The top layer represents the transit agency that aims to maximize system efficiency, as represented by the transit network design problem. Supply and demand interact between each layer, determining the overall system state. In this report, we describe the overall design of that system followed by the findings of two case studies: one to identify microtransit service areas and one to study the use of microtransit and ride-hailing by wheelchair users. We also describe an extension to develop an transferrable model of ride-hailing demand.

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Publications

A report further describing Case Study 1 was published as:

> Macfarlane, Gregory S., Atchley, H. (2022). Identifying Microtransit Service Areas through Microsimulation. Utah DOT Report number UT23-01. https://rosap.ntl.bts.gov/view/dot/66312

A report further describing Case Study 2 was published in a report by our partners at the Utah Department of Transportation:

> Macfarlane, G. S., & Lant, N. J. (2021). *Estimation and Simulation of Daily Activity Patterns for Individuals Using Wheelchairs* (UT-21.10). https://rosap.ntl.bts.gov/view/dot/56982

Additionally, the findings of this research were presented at the 12th International Scientific Conference on Mobility and Transport (MobilTUM) hosted by the Technical University of Munich:

> Macfarlane, G.S., & Lant, N.J. (2022). How far are we from transportation equity? Measuring the effect of wheelchair use on daily activity patterns. In *mobil.TUM 2022 – 12th International Scientific Conference on Mobility and Transport*. Lectern presentation. Singapore.

A paper of the research is included in the forthcoming *Lecture Notes in Mobility* series published by Springer at https://link.springer.com/book/9789811983603

Extension 1 is in-review for publication by *Transportation Research Record*, with the submitted manuscript freely available online. The recommended citation is:

> Mucci, R.A., Erhardt, G.D. (in-review) "Ride-Hailing Sharing and Matching in Chicago: Travel Time, Cost, and Choice Models" in-review by *Transportation Research Record*. Also published in the 2023 Compendium of the Annual Meeting of the Transportation Research Board. Full paper available for download here: https://tscore.gatech.edu/publications/

In addition, a paper describing the implications of the data suppression strategies used to protect user privacy is published in *Transport Findings* and available open-access at:

> Mucci, R.A., and G.D. Erhardt. (2022) Ride-Hailing Data Suppression and Exclusion Strategies Can Lead to Biased Outcomes. *Transport Findings*. https://doi.org/10.32866/001c.34191.

Together, this research will be reflected in the PhD dissertation for T-SCORE graduate student researcher, Richard Alexander Mucci, which we expect to be freely available online in mid-2023:

> Mucci, Richard Alexander. *Transferrable Models of Ride-Hail Demand*. PhD Thesis, University of Kentucky, 2023. https://uknowledge.uky.edu/ce_etds/.

Introduction

The Tier 1 University Transportation Center known as Transit – Serving Communities Optimally Responsively and Efficiently (T-SCORE) was a consortium from 2020 to 2023 led by Georgia Tech (GT) that included research partners at University of Kentucky (UK), Brigham Young University (BYU) and University of Tennessee, Knoxville (UTK). The investigators from each university are:

1. **Georgia Tech:** Dr. Kari Watkins (Center Director, now at University of California, Davis), Dr. Michael Hunter, Dr. Pascal Van Hentenryck, and Dr. Srinivas Peeta
2. **University of Kentucky**: Dr. Gregory Erhardt
3. **Brigham Young University**: Dr. Gregory Macfarlane
4. **University of Tennessee**, Knoxville: Dr. Candace Brakewood, and Dr. Christopher Cherry

The overarching goal of the T-SCORE research center was to define a set strategic visions that will guide public transportation into a sustainable and resilient future, and to equip local planners with the tools needed to translate their chosen vision into their own community. The research approach for the T-SCORE center is shown in Figure 1. The research began with a strategy generation stage, which generated qualitative descriptions of strategic directions that transit agencies and their partners can take for further evaluation. These strategic visions fed into a two-track research assessment that includes a Community Analysis Track (led by Dr. Candace Brakewood at University of Tennessee) and a Multi-Modal Optimization and Simulation (MMOS) track (led by Dr. Greg Erhardt at University of Kentucky). Both of these tracks aimed to identify the potential feasibility, benefits, costs and implications of each strategic vision, such as on-demand transit services or new fare policies. These tracks came together in the final strategy evaluation stage, in which the findings were again considered in the context of expert advice, as shown in Figure 1. More information about the various research activities conducted as part of the UTC Tier 1 center can be found on the T-SCORE website hosted by Georgia Tech: https://tscore.gatech.edu/

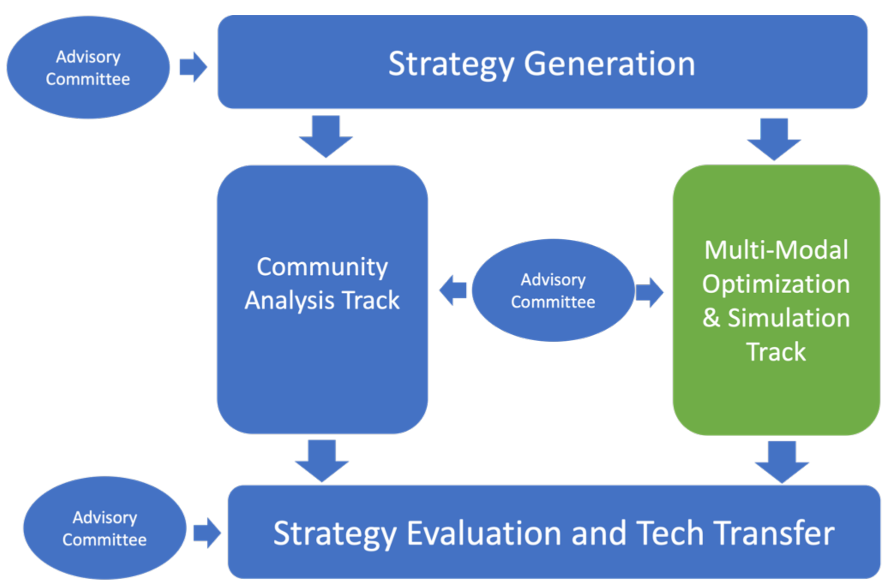

Figure 1: Overarching Research Approach for the T-SCORE Center

The focus of this Final Report is the MMOS research track (highlighted in green in Figure 1). The MMOS research track implemented bleeding-edge simulation and optimization techniques to model, forecast, and understand the relationship between traditional and novel public transportation services. The goal of this research was to develop tools that researchers and public agencies can use to develop policies related to new transit modes including agency-organized microtransit services and privately run ride-hail services, and to apply those models to gain insight into both types of services.

The MMOS track's research approach was divided into four separate research projects on these key topics. These four projects (numbered M1-M4) are briefly described in Figure 2 below. These four research projects are strongly related and were completed by an integrated research team consisting of T-SCORE researchers and our partners. This report provides the holistic description of the relationship between these four projects.

M1: Multi Modal Optimization

- Project M1 focused on developing software tools and optimization models for the design of publicly-operated on-demand multi-modal transit systems.

M2: Multi Agent Simulation

- Project M2 focused on developing and applying agent-based simulation models to better understand the behavior of private ride-hailing and its effect on the transportation system.

M3: MMOS Integration

- Project M3 focused on better understanding the relationship between private ride-hailing and public transit through improved models and data.

M4: Implementation and Quantitative Evaluation *(This report)*

- Project M4 focused on applying the above tools to realistic scenarios in multiple cities to gain insights into the effective design of transit systems.

Figure 2: MMOS Track Research Projects

Project M4: Implementation and Quantitative Evaluation

This Final Report presents the outcomes of MMOS track project M4 that focuses on applying the tools developed in projects M1 through M3 to realistic scenarios in multiple cities. These analyses provide insight into the effective design of transit systems, including on-demand transit systems. In this final report, we first describe the research motivation and provide an overview how the different models and components fit together to form a combined Multi-Modal Optimization and Simulation research track. Then we describe two case studies and one extension that apply these tools to gain different insights into the system. These case studies are shown in Figure 3 and summarized in the remainder of this report.

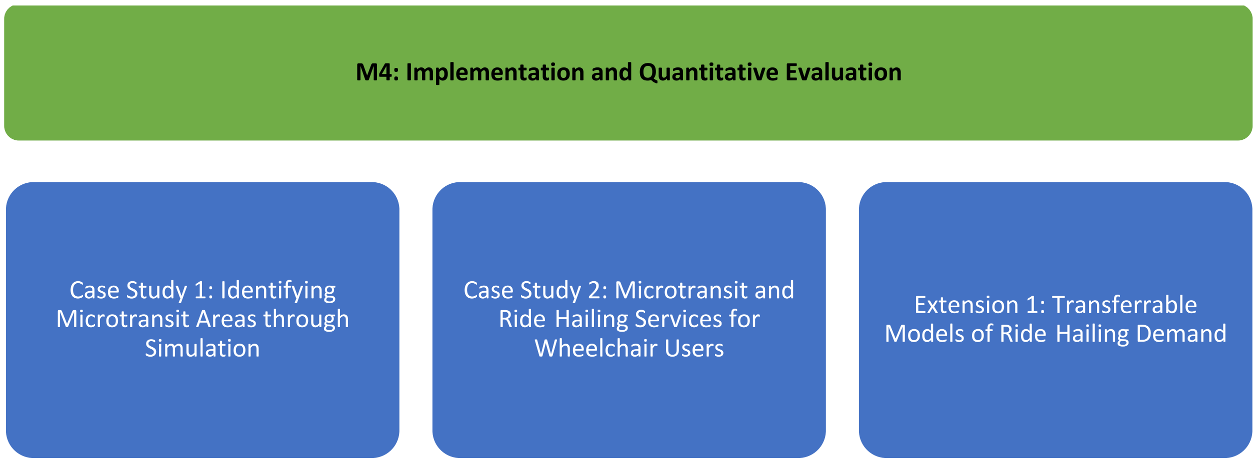

Figure 3: M4 Research Projects applying MMOS Tools to Case Studies

Problem Description

Public transit is currently facing tremendous challenges. During the COVID-19 pandemic, ridership is down 30-50% in European cities and down up to 70% in US cities (L. Liu et al., 2020; Rasca et al., 2021), and its long-term recovery remains uncertain given potential for continued telework, especially among workers in central business districts (Currie et al., 2021). Even before the pandemic, bus ridership in the US had decreased 15% since 2012 and rail ridership had decreased 3% (Watkins et al., 2022). These pre-pandemic ridership losses are specific to the US context, and recent research suggests that competition with ride-hailing is the largest contributor to those declines (Erhardt, Hoque, et al., 2022; Erhardt, Mucci, et al., 2022; Watkins et al., 2022), resulting in more traffic congestion for all road users, including those who remain on the bus (Erhardt et al., 2019). Despite these challenges, public transit remains a vital service, especially for many essential workers and low-income individuals who are more likely to remain on transit (Hu & Chen, 2021; Monahan & Lamb, 2022). Also, to reach the goals of the Paris climate agreement, an increase of transit ridership will be required, as the average transit trip generates about 1/8 of CO_2-equivalent emissions of the comparable car trip (Llorca et al., 2020).

Much of the research on ride-hailing and transit focuses on whether ride-hailing complements or competes with transit, with a growing consensus that it does fill some gaps where transit service is poor (Cats et al., 2022; Young et al., 2020), but also that the net effect is less transit ridership with a bigger effect on bus than rail (Clewlow & Mishra, 2017; Diao et al., 2021; Erhardt, Mucci, et al., 2022; Ward et al., 2021). The differing effect by travel mode may be due to rail's travel time advantage, or that it often serves longer trips. Either way, that distinction offers hints to the types of transit service that remain most attractive when ride-hailing operates in the same city. The effect likely also varies based on travelers' characteristics. Transit planners have long distinguished between "choice" and "captive" riders based on their ability and resources to switch to a different mode (Keefer, 1962), and we may reasonably expect travelers with higher incomes tend to be choice rides and more willing to switch from transit to ride-hailing.

At the same time, researchers and transit operators are considering the potential of On-Demand Multi-Modal Transit Systems (ODMTS) that combine fixed-route transit in high-demand corridors with on-demand shuttles serving a first and last mile role or serving low-density areas (Auad & Van Hentenryck, 2021; Y. Liu & Ouyang, 2021). ODMTS is distinct from ride-hailing because the passenger routing is managed centrally to improve overall system efficiency. For example, in ODMTS, the routing may force a passenger to transfer from a shuttle to a bus in a congested corridor, whereas a ride-hailing company's routing may book the entire trip in a car both because it increases their own profit and because it saves the passenger a transfer.

Figure 4 illustrates the distinction between ride-hailing and ODMTS, which is both technical and institutional. Thus, there are three different types of actors, each with a different incentive. The traveler seeks to maximize their own utility, the ride-hailing company seeks to maximize their own profit, and the transit operator aims to provide a broadly available service and manage system efficiency. Models that do not account for competition from private mobility providers are inherently limited unless those providers do not operate in the system.

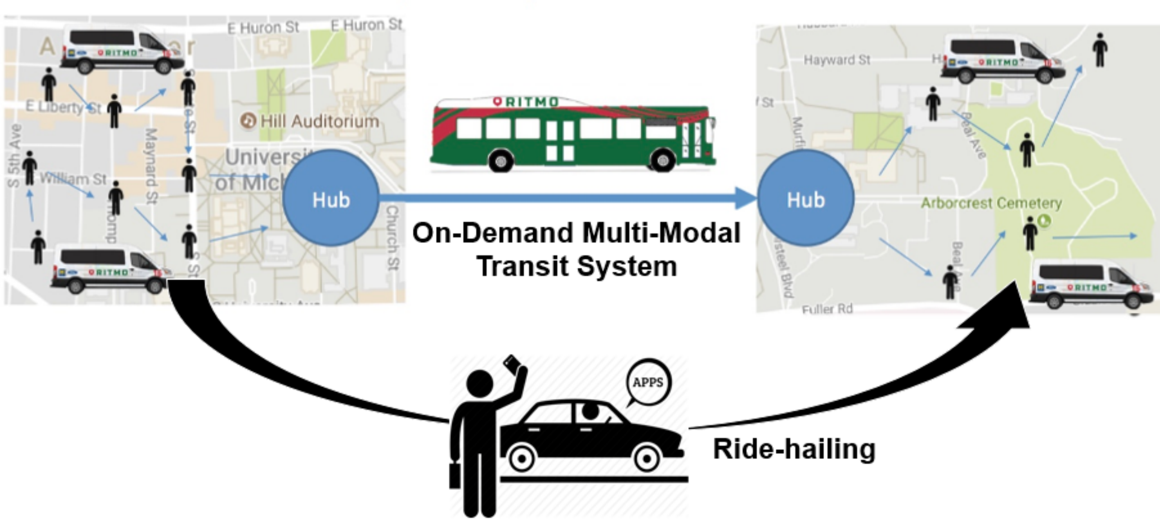

Figure 4: Both ODMTS and ride-hailing rely on small on-demand vehicles, usually vans or passenger cars, but they operate differently. Ride-hailing companies and drivers operate independently to maximize their own profit, often competing in corridors already well-served by transit. In contrast, an ODMTS requires centralized dispatching and routing of micro-transit vehicles. They are optimized for social benefit (maximize ridership, minimize congestion).

How can transit operators respond to these challenges and potential opportunities? The transit network design problem is useful for determining the service provision by fiding the optimal headways for each line in a transit network (LeBlanc, 1988) or by finding how to integrate fixed-route transit with on-demand shuttles (Auad & Van Hentenryck, 2021; Y. Liu & Ouyang, 2021). As the transit supply changes, demand will change in response, affecting the optimal network design (Lee & Vuchic, 2005). However, due to the complexity of solving an ODMTS design, recent examples either hold the transit demand fixed (Y. Liu & Ouyang, 2021; Luo & Nie, 2019) or treat it with a simple homogeneous elasticity.

In contrast, a new generation of travel demand models has emerged that provide a more realistic representation of travel behavior (Castiglione et al., 2014; Moeckel et al., 2020) and routing through a multi-modal network (Horni et al., 2016; Sheppard et al., 2017). An important feature of these models is that they do a better job of capturing the heterogeneity—such as differences in income, car ownership, and activity timing constraints—that affects the choice to use transit (Moeckel et al., 2017). Also, because these models are agent-based simulations they can represent the matching that occurs between passengers and ride-hailing or demand-responsive transit vehicles (Bauer et al., 2019; Bischoff et al., 2016; Zwick et al., 2021).

In this research, we combine the transit network design problem with an agent-based travel demand model and a simulation of ride-hailing behavior into a combined Multi-Modal Optimization and Simulation Framework.

Approach and Methodology

The T-SCORE research team developed a Multi-Modal Optimization and Simulation (MMOS) framework that will serve as the starting point for analyzing the case studies described later in this report. The MMOS combines three layers, each representing a different type of actor, as shown in Figure 5. The central layer represents travelers who aim to maximize their own utility. It includes two modeling components: an activity-based model of travel demand generates the daily travel plans for a synthetic population of a city, and a multi-agent simulation predicts how those agents move through a multi-modal network and the congestion impacts as they do so. The bottom layer represents behavior of private mobility providers, such as ride-hailing drivers, that aim to maximize their own profit. The top layer represents the transit agency that aims to maximize system efficiency, as represented by the transit network design problem. Supply and demand interact between each layer, determining the overall system state.

The traveler layer uses an activity-based travel demand model to generate a synthetic population with demographic information, home locations, the activities they participate in (work, school, shopping, etc.), and the order, timing and destinations of those activities. ActivitySim is used because it is open-source and can be readily implemented for new regions (ActivitySim, n.d.). These activity plans are fed to the Behavior, Energy, Autonomy, and Mobility (BEAM) model to simulate how travelers move through a multi-modal network (Sheppard et al., 2017). BEAM predicts the mode, route and precise departure time of each trip, the vehicles used, and congestion caused by those vehicles. In Project M3 we consider how these tools fit together, specifically in their treatment of mode choice, and evaluate the implications of modeling mode choice for ride-hailing and on-demand transit in each framework.

For the private mobility provider layer, BEAM simulates the behavior of ride-hailing passengers requesting rides, and drivers accepting those rides, but the driver fleet is specified exogenously. Therefore, a separate model is developed in Project M2 to predict the location, start time and duration of ride-hailing driver shifts using a unique data set of ride-hailing driver behavior (Cooper et al., 2018).

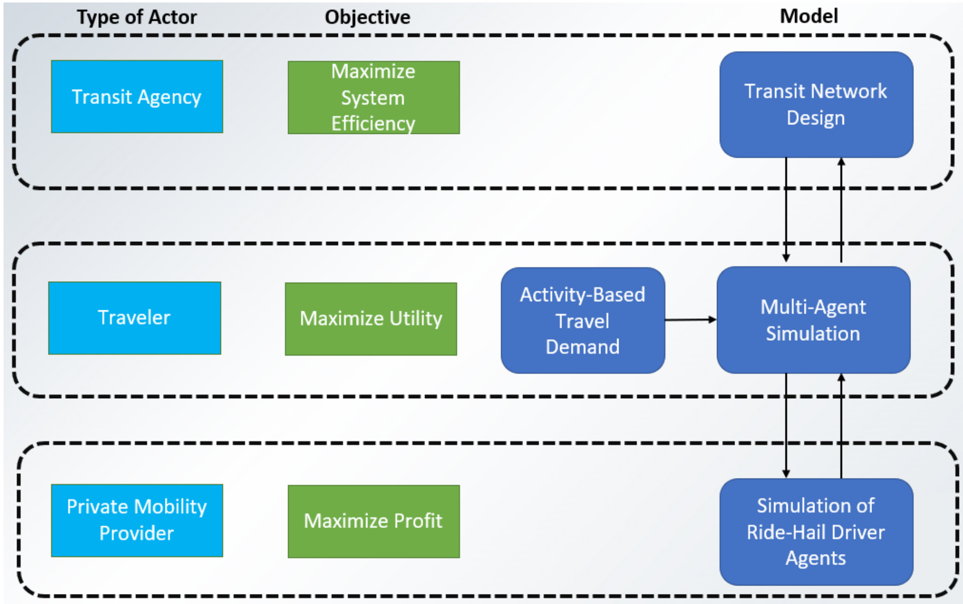

Figure 5: Different types of actors, each with their own objectives, combine to influence transit system outcomes.

The transit agency layer is uses optimization methods to design On-Demand Multi-Modal Transit Systems (Auad & Van Hentenryck, 2021; Basciftci & Van Hentenryck, 2020, 2021). This layer accepts as input the origin, destination and departure time of agents using transit, the congested roadway network, and a "backbone" network of fixed-route transit lines. The optimization produces a recommended transit network that combines service on the backbone routes, new fixed-route bus service, and on-demand shuttles. The design balances minimizing traveler cost and user cost and can include a simple representation of the demand elasticity (Basciftci & Van Hentenryck, 2021). In Project M1, we implemented several enhancements to this structure, adding the capacity for walk transfers, weighted time paths, and improving its usefulness for large cities.

The team applied these tools to multiple case studies. We use the simulation tools to study microtransit service areas and the provision of microtransit service to wheelchair users in Utah. We implemented the combined models for comprehensive case studies in San Francisco and Salt Lake City. In a match project that recently started, we will study how different levels of ride-hailing competition affect transit network design.

Findings for Case Study 1: Identifying Microtransit Areas through Simulation

In 2019, the Utah Transit Authority launched an on-demand transit service in south Salt Lake County, Utah in cooperation with Via, a private mobility company. On-demand transit services—sometimes referred to as microtransit—are a mobility service in which passengers request shared rides from shuttles through a mobile application. Such microtransit services are relatively new, as the increasing penetration of smartphones and other location-aware mobile devices has enabled such services and created a larger potential market. Such systems hold great potential for improving first- and last-mile access to fixed route, mass transit systems and for enhancing mobility for households with limited automobile ownership (Shaheen et al., 2015). Initial research on such systems has included efforts to understand attitudes and preferences for such a system (Macfarlane, et al., 2021) as well as general operations and utilization (Alonso-González et al., 2018). Many questions remain, however, about the long-term sustainability of such systems, and there are systems that have succeeded as well as those that have failed (Alonso-González et al., 2018; Helsinki Transit, 2016). Developing demand forecasting frameworks to understand and model these systems prior to deployment will improve the likelihood of successful deployments.

While some attempts have been made to model demand for microtransit, tools and practices to do this are still in the early stages of development. In this project, we apply the BEAM (Lawrence Berkeley National Laboratory, 2022) demand microsimulation framework to model ridership and wait times for the 2019 deployment in south Salt Lake County. The model produced daily ridership estimates and utilization rates in line with the observed data collected from the system between November 2019 and March 2020 (prior to the arrival of COVID-19 in Utah). We then apply this same model to several potential expansion areas along the Wasatch Front. The model suggests that demand for the service is limited primarily by the resources allocated to it, with ridership scaling linearly with the number of vehicles in service. There are, however, unresolved methodological questions surrounding simulation scaling – how to appropriately scale down microtransit fleets with small numbers of vehicles and small capacity is an open research question. Similarly, the procedures by which BEAM identifies modes for its agents is constantly evolving in search of improved methods. Despite these limitations, the simulation models suggest that households with low vehicle ownership are most likely to use the service.

The results at face value suggest that microtransit may in fact work in any of the study regions, as BEAM predicts that the microtransit fleets are fully utilized in each scenario. The results also provide an illustration of the potential benefits of microsimulation for travel demand analysis, with the model providing an understanding of who is using the services and for what purposes. Further research is required, however, to develop the simulation inputs, refine methodologies, and analyze and interpret outputs.

Findings for Case Study 2: Mictrotransit and Ride-Hailing Services for Wheelchair Users

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.

Findings for Extension 1: Transferrable Models of Ride-Hailing Demand

Ride-hailing is a relatively new but rapidly growing mode of travel. Understanding and predicting ride-hailing demand is important to transportation planners who may use such data to evaluate the externalities of ride-hailing trips, adapt urban street design to accommodate ride-hailing trips, or to evaluate ride-hailing policy changes. Detailed ride-hailing data is unavailable in most cities, which leaves planners in those cities unable to build models for this important mode. This research aims to develop a transferable model of ride-hailing data that uses open-source data and has the ability to predict ride-hailing demand for any city in the United States.

Chicago is one of a few cities that have mandated ride-hailing companies to submit detailed data of their trips to the local transportation agency. The dataset is one of the few to contain trip level attributes such as fare, travel time, and trip length. We estimate a model of ride-hailing demand using the Chicago ride-hailing data, as well as associated open-data from the American Community Survey, the Longitudinal Employment-Household Dynamics data, OpenStreetMap and the General Transit Feed Specification. By using these open-data sources as predictive variables of ride-hailing use, the model can be applied to any region in the United States. The model operates at a Census tract level, considers both origins and destinations, and is time-of-day specific.

This study addresses important limitations of the data that hold the potential to bias the results. To protect privacy, locations and times in the Chicago ride-hail data are aggregated, and locations are further suppressed when the frequency of trips is low. Most researchers using this data remove the trips with suppressed locations or external destinations from their analysis. This research finds that when suppressed and external trips are excluded, the trip length, cost, and distance are all underestimated, as are trips in low-income neighborhoods. In this research, we develop a method to include those trips at a more aggregate spatial resolution.

The study examines on why ride-hailing passengers use shared or private ride-hailing trips and what causes the shared trips to be matched. The results show that trips to/from airports are less likely to be shared and trips to/from low-income areas are more likely to be shared. Longer shared trips are more likely to be matched, shared trips to/from dense areas are more likely to be matched, and shared trips between areas with a high number of commuters is more likely to be matched. Each additional shared trips being matched together is found to add approximately 4 minutes to a trip. Ride-hailing users' value of time is found to be $48.23 per hour when choosing between shared and private rides.

The ability to predict ride-hailing ridership for all Census tracts in the United States will allow more cities to understand ride-hailing demand and its associated impacts in their community. The results of this research can be applied to test polices aiming to promote more sustainable transportation modes.

Conclusions

In this project, we developed and applied a framework for modeling the relationship between three types of actorss influencing transit system outcomes: transit agencies, travelers, and private mobility providers. By understanding the interactions among these actors, we can gain insight into how to effectively design transit networks. We applied this tool to two case studies.

In the first case study, we used these tools to identify potential microtransit service areas. Our analysis suggests that demand for the service is limited primarily by the resources allocated to it, with ridership scaling linearly with the number of vehicles in service. In the second case study, we studied the demand for microtransit and ride-hailing services among wheelchair users. We found that wheelchair users are less likely to leave home on a typical weekday, presumably due to the difficulty of doing so. We tested the effect of providing on-demand microtransit trips to wheelchair users and found that the demand scaled linearly with the amount of service provided. In both cases, further investigation is needed to understand the limits of these findings and explore their sensitivity to varying assumptions. In both case studies, the outcome of demand scaling with supply is desirable for travelers who would benefit from the service, but come at a cost to the operator who would budget the service.

In an extension to these tools, we developed a transferrable model of ride-hailing demand, estimated from observed ride-hailing data in Chicago. We examined in detail users' choice of whether to request a private ride or a shared ride, and if they select a shared ride, whether they are matched with another passenger. The resulting model appears to reasonably match the observed travel patterns and can be applied throughout the United States using publicly available data. Further study is needed to evaluate the validity of the model when applied to a new location.

Recommendations

The results of this study have implications for transit planning in the United States. The nature of on-demand transit demand scaling with supply suggests that operators considering such service should identify ahead of time how they will deal with potentially rising costs. Reasonable actions could be capping the cost and letting wait times increase, increasing the price, or serving only specific users or specific types of trips.

In modeling ride-hailing demand, we found that ride-hailing is most common in dense areas and higher income areas, but that trips with an origin or destination in low-income areas are more likely to request a shared ride. Unfortunately, the places where users are most likely to request a shared ride do not always align with the places where shared riders are most likely to be match with other riders, simply because the overall demand is lower. Therefore, cities should consider ways to incentivize shared rides in the highest demand areas. One way to do so is by increasing the price difference between private and shared rides. The high values of time estimated from these data suggest that the price differential must be substantial to result in a noticeable shift in behavior.

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