Estimating Activity and Health Impacts of First and Last Mile Transit Access Programs for Work and Shopping Trips Using Sharing Mobility Services in the Metropolitan Area

Center for Transportation, Environment, and Community Health
Final Report

by:

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DISCLAIMER

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16. Abstract
This study evaluates the benefits of a first mile transit access program using shared mobility services. In doing so, the authors introduce a novel simulation and optimization framework that integrates macro-simulation of travel decisions to evaluate the mode choices for work and shopping trips. Specifically, to identify the potential demand shifts from drive alone mode to the proposed ridesharing and transit program. For the shifting individuals, a continuous location-allocation optimization model finds the optimal location of pick-up and drop-off (PUDOs) points where the ridesharing services picks-up the users and transports them to public transit stations. An agent-based simulation explicitly models the pick-up and transport activities. Finally, the framework evaluates the health benefits using the Integrated and Health Impacts Model (ITHIM).
The framework allows estimating transit, travel, access, and waiting times, health impacts and costs. The results provide insights for planners and policy makers to better understand the system performance, recognize the gaps and provide solutions effectively.

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Introduction and Background

A vehicle-centric system and low average vehicle occupancies significantly contribute to traffic congestion and pollution in many urban areas (Schrank et al., 2015; Davis et al., 2016). Consequently, private vehicles generate the largest share of greenhouse gas (GHG) emissions in the transportation sector (Edenhofer et al., 2014). For many years, transportation engineers, planners, academics and public agencies have tried to address this issue by developing a number of strategies from infrastructure to demand management. In most cases, the priority is to promote active modes and public transit, and increase vehicle occupancy.

Recently, the advent of pooled ridesharing services provides an opportunity to mitigate the impacts of low occupancy rates, and the revolution brought about by these new service providers seems to be able to overcome the limitations of decade long pool-type strategy efforts. However, the ideals have not fully materialized and there is a general lack of research regarding their effectiveness.

Ridesharing refers to a transportation mode in which people having similar travel itineraries and schedules share a vehicle for a trip and possibly split the associated costs. Technology and the shared economy have enabled these services with real-time matching of on-demand requests to drivers. In many cases, these services have become an additional travel option with no significant improvements on vehicle miles/hours traveled (VMT/VHT). Some studies even show evidence of transit demand going to these services (Rayle et al., 2016; Clewlow and Mishra, 2017; Henao, 2017; Alemi et al., 2018). This unintended consequence has important implications, as it affects the transportation system, in general and public transit, in particular.

Nevertheless, there is still a great deal of interest about the potential of these services to improve the system. There are a number of urban and rural regions in the U.S. studying and pilot testing the integration of these services in the multi-modal transport system, specifically as part of transit access systems. These studies are trying to determine the feasibility and impacts through partnerships between the agencies and shared mobility providers.

This project builds on previous work (Jaller et al., 2018) evaluating the benefits of a first mile transit access program using shared mobility services, focusing on the potential demand shifts from drive alone mode to this program. Specifically, the program is a combination of ridesharing and pooling where individuals walk to a mutual pick-up and drop-off (PUDO) meeting point and pool the ride to the transit station.

The authors expanded the previously developed simulation and optimization framework to evaluate the program, and assess the health impacts. Similarly, the authors conduct a case study in the San Francisco Bay Area. In general, the new framework has four main components. The first component includes a macro-simulation of long- and short-term travel decisions using the Metropolitan Transportation Council Activity-based Travel Model One (MTC-ABM). The second is an optimization tool that identifies the PUDOs and allocates the demand. The third uses the Multi-Agent Transport Simulation (MATSIM) model to simulate the movements from origins to PUDOs, and then to BART stations. Finally, the framework uses the Integrated and Health Impacts Model (ITHIM) to estimate system-level health impacts.

This study focuses on work and shopping related trips in the study area for specific simulation time periods. Each of the framework components offers insights into the potential demand for the integrated first mile transit service. The results show that while there could be a modest shift to the service, especially from drive alone users, still the impacts are very small, which translates into almost negligible health impacts. Nevertheless, there could be localized health and emission impact reductions.

The report is organized as follows. Section 2 provides a succinct literature review on the different methodologies used to model shared mobility services. Section 3 describes the framework and data. Section 4 discusses the results of the various analyses. The report ends with a summary of key findings.

Background and Literature Review

Transit agencies have long realized the efficiency and effectiveness of conventional fixed-route fixed-schedule services in dense urban areas; however, these services are very expensive and inefficient in less dense and suburban areas. Feeder systems and other strategies (e.g., Park-and-Ride) have tried to address the gap for first and last mile access. Park-and-ride and other parking structures, for instance, are very expensive and usually only provides a temporary solution as capacity is quickly overrun.

In this sense, the advent of shared mobility services offers a new alternative, and agencies throughout the country are exploring the integrated services (ridesharing and transit) for the first and last mile; though with mixed results. In some cases, the private business efforts have not been able to foster user participation in shared services (while they have been very effective at attracting "single[1]" users). In other cases, the integration may add constraints of the transit service to the equation.

Alemi and Rodier (2018) evaluated the potential demand for the San Francisco and compared simulated travel times (from MTC-ABM) with those reported by real-time mapping services, and shared mobility service providers. Other authors have studied the relationship between shared services and transit, and the use of autonomous vehicles as part of the system (Cervero, 2001; Martin and Shaheen, 2014; Hoffmann et al., 2016; Rodier et al., 2016; Bischoff et al., 2017a). The literature discussed here focuses on shared mobility (ridesharing specifically) and optimization methods to address the problem. While there is a vast literature on transit network design, it is out of the scope of this project.

Related to ridesharing, most of the studies evaluate decentralized door-to-door services. Agatz et al. (2011) developed an integer programming optimization model to deal with a single rider dynamic ridesharing problem with a rolling time horizon where each participant had a time window and announcement lead-time. Riders own a car and are interested in round-trips. The proposed optimization approach increased the matching rate, and led to larger system wide VMT savings compared to a simple greedy algorithm. The approach showed that dynamic ride sharing has the potential to be successful in urbanized areas even with low participation rates. Later, Agatz et al. (2012) conducted a comprehensive literature review on dynamic ridesharing optimization methodologies. Similarly, Furuhata et al. (2013) studied different types of ridesharing and discussed their characteristics, challenges and opportunities. Several other studies have developed models and algorithms for the ridesharing problem under different assumptions (Santos and Santos, 2015; Meng et al., 2016).

Thaithatkul et al. (2016) studied ridesharing considering passenger's preferences, between ridesharing and drive alone for single occupancy vehicles. It has a two-step time horizon framework that uses a travel utility function to match users based on their preferences. Applying the model to a randomly generated dataset showed an average cost reduction of 45%, but did not reduce waiting times from the base case

Stiglic et al. (2016) studied matching flexibility, detour flexibility, and scheduling flexibility, on a single-driver, single-rider ride-sharing system. The objective of the work was to design incentives programs based on user's flexibility. It assumed deterministic and static supply and demand

[1] Here "single" includes an individual or groups already traveling together.

patterns. The model should establish the matching before a driver's departure time. Feasible matches are those in which the difference between the joint individual direct distance and the total distance of the driver is positive. The major finding was that moderate levels of matching flexibility, particularly from driver side, is necessary for ridesharing to work effectively even at high participation rates. Alonso-Mora et al. (2017) solved a dynamic high-capacity ridesharing problem applicable to shared autonomous vehicle fleets, and tested the proposed model using taxi data from New York City. The results showed that shared services could reduce the trips by 77%.

About the specific topic of this project, Stiglic et al. (2018) addressed the problem of integrating a ridesharing service with public transit. They implemented a proposed model to a hypothetical network considering a set of different types of public transit systems (e.g., commuter rail and urban rapid transit). Their work assumes ridesharing activities, but not necessarily a ridesharing service. They concluded the integrated mode could increase the matching and reduce detour distances, particularly if the driver also uses the transit, or if the driver is willing to service more than one rider.

These works have used different types of optimization concepts and methods. Considering the scope of the proposed simulation framework, this study focuses on approximation techniques that could bridge the different types of simulation (large-scale activity based- and agent-based modeling). Some of these techniques fall under continuous approximation models, which have been extensively used in transportation, especially for facility location problems. For instance, Li and Ouyang (2010) modeled a reliable location problem where facilities can fail using continuous approximation. The objective of the work was to minimize the total cost including the fixed facility opening cost, penalty cost for rejected customers and transportation cost for served ones, under the disruption scenarios. Jaller (2011) also used continuous approximation techniques to identify the optimal location of distribution facilities where individuals had to walk to access the goods provided. The model estimates the number of facilities, their capacity, and distribution strategy minimizing total social costs, which include both logistics and external costs.

Similarly, Yushimito et al. (2012) solved a non-capacitated facility location problem considering a continuous demand function. The authors developed Voronoi-based heuristic and evaluated different sampling methods to improve the algorithm accuracy.

Tsao et al. (2012) developed an integrated facility-inventory allocation problem minimizing total transportation and inventory costs. They used a two-stage continuous approximation technique, and estimated distances in Euclidean norms using Daganzo and Newell (1986) approximations. Another application of continuous approximation include Huang et al. (2013)'s work on the vehicle routing problem. They approximate travel time for each vehicle using a slow varying demand density function and distances. They compared their approximate model with other routine techniques, and showed their benefits.

Finally, the authors present preliminary findings from this project in Jaller et al. (2019).

Methods and Data

As mentioned before, the updated proposed framework has four main components: 1) Macro-simulation of travel decisions using the MTC-ABM *Model One*; 2) continuous location-allocation optimization model to find the optimal PUDOs; 3) agent-based analysis using MATSIM model; and 4) health impacts through ITHIM. FIGURE 1 shows the diagram of the framework.

Macro-Simulation (Activity-Based) and Scenario Analysis

This component analyzes the mode and destination choice models in MTC-ABM to identify the factors influencing choice decisions. This is important to accurately modify the embedded models in the MTC-ABM to simulate transit access through shared mobility services. The process modifies the utility functions of using heavy rail (i.e., BART) based on a series of scenarios. The scenarios test the sensitivity of the choice decision to use the shared service. This helps identify potential participants for the transit access ridesharing service, or "ridesharing+transit". Although the framework is general, in this project, the authors focused on work and shopping trips during specific periods of the day. For example, the authors concentrated on:

- AM Peak work trips;
- Midday shopping trips; and
- Midday work and shopping trips.

The mode choices in MTC-ABM follow nested logit structures with utility functions consisting of traveler characteristics, trip purpose, and mode specific variables and skims. The mode choice models evaluate choices for 18 different travel modes (e.g., drive alone, passenger ride, active, and a combination of access modes and transit services). The MTC-ABM does not include shared mobility services, thus the team modified (using proxies) the existing choice models to represent the ridesharing+transit service. Specifically, the team concentrated on the existing "drive to heavy rail (i.e., BART)."

Following the work in Jaller et al. (2018), FIGURE 2 shows the values used to modify the utility functions. For example, the authors assumed a minimum age of 13 to use the service because ridesharing does not require driving for the passenger. Similarly, using the service does not require owning a vehicle (households without a car can access the service). The authors assumed a number of scenarios to simulate transit accessibility by modifying the driving (access) times and costs. Reducing driving time reflects the convenience of travel without needing to drive. Considering the service would require out-of-pocket expenses, the authors also assumed cost increases. In FIGURE 2, "S" refers to the magnitude of change that could produce a significant shift to this mode. The authors assumed a value of S between 0 and 1 for drive time, and between 0 and 2 for costs. Moreover, there are a few studies evaluating the impacts of Value of Time (VOT) for passengers compared to drivers and for passenger while traveling in public transit (Fosgerau et al., 2007; Román et al., 2007; Batley et al., 2010). The studies showed that passenger VOT is (perceived) about 65% to 85% that of driver. Finally, having access to transit through ridesharing eliminates the burden of driving, and changes its perceived in-vehicle value of time from the drivers' to the passengers' perspectives. The authors modeled the scenarios and compared the results with the 2010 baseline MTC scenario. To isolate the impacts of the parameter changes, the authors fixed long-term choices for work and school location choice, auto ownership, and daily activity patterns for each individual.

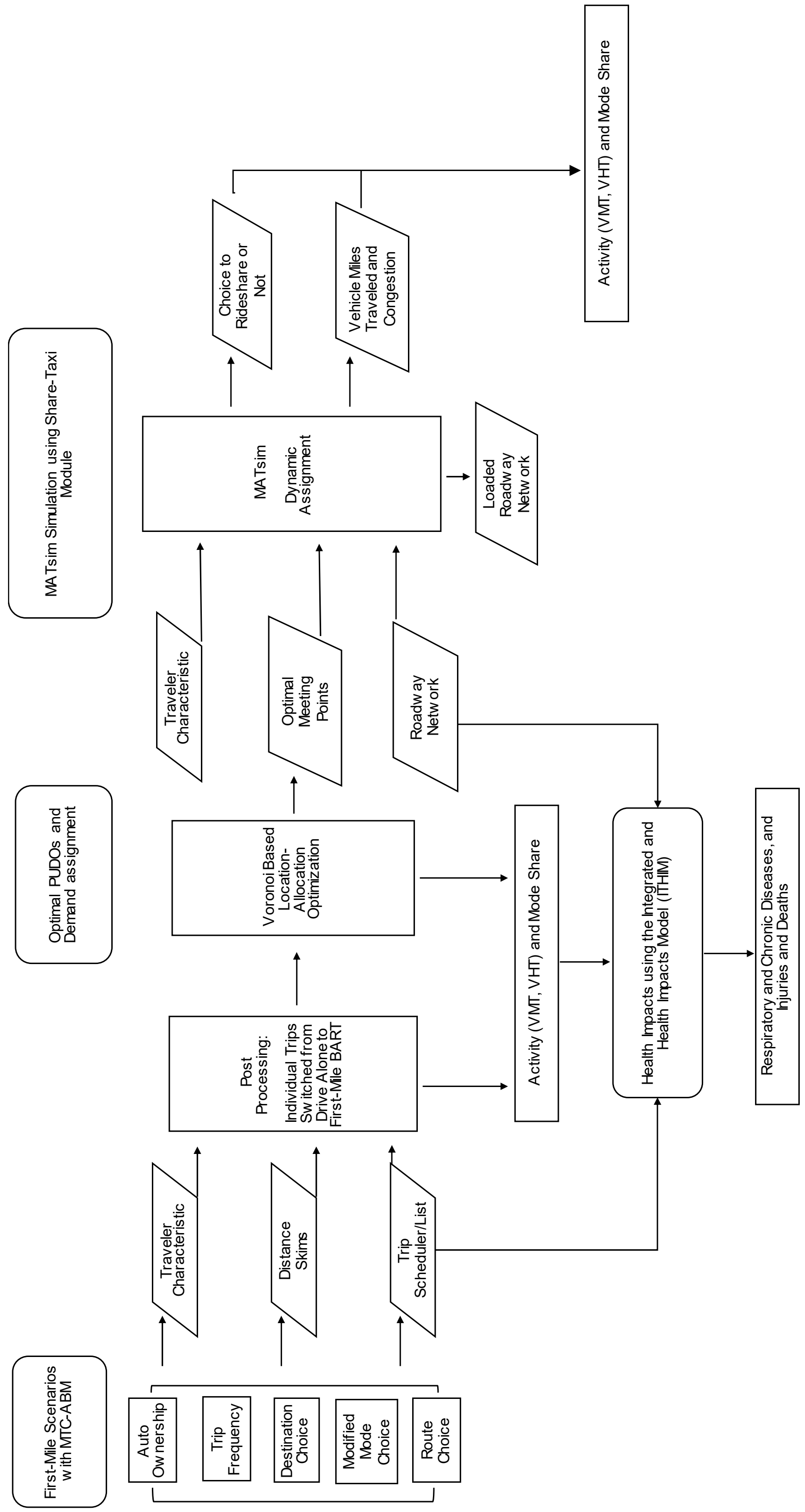


FIGURE 1 Proposed Framework (Updated from Jaller et al. (2018))

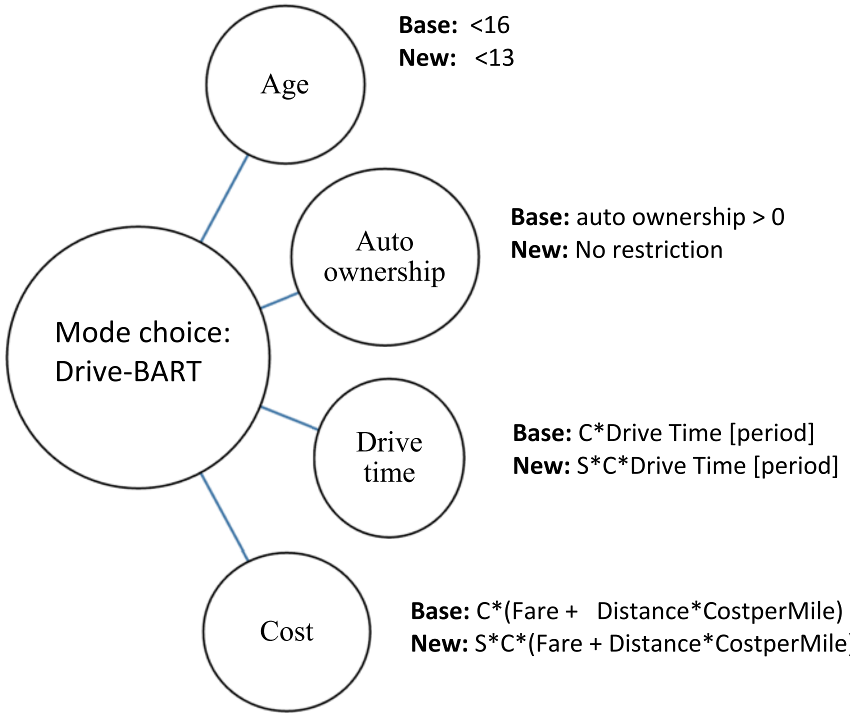


FIGURE 2 Parameter changes and scenarios

Determining the Location of the PUDOs

When identifying the optimal location of PUDOs for the ridesharing+transit service it is important to consider the various aspects of the transport activity, such as the concentration of demand, the relative location of the PUDO to the transit station, the willingness of individuals to walk and wait, and other travel decisions.

In this work, the optimal location minimizes total travel distance to the PUDO from the users' origin, f^a, and the vehicle distance from its initial location to the PUDO, f^{dr}. The relationship between these two distances, converted to time, would affect both the access time, and the waiting time for service, f^w. Moreover, the location should also consider the in-vehicle traveled distance (or time) from the PUDO to the transit (i.e., BART) station. The waiting time at PUDO, as discussed before, refers to the time an individual may have to wait for the other users or the vehicle to arrive at the PUDO.

The authors assumed that there are enough vehicles (unlimited supply) in the system to provide the service, and conducted scenarios analyzing the initial position of such vehicles. Vehicle positions include the transit station, near or at the PUDO, or somewhere between the station and the demand point. This evaluation framework assumes that there would be available capacity to meet the demand, and that service providers will optimize the location of the vehicles (and repositioning) once they understand demand patterns.

The reader is referred to Jaller et al. (2018) for a general description of the optimization model. In general, the model (assuming known travelers' location) identifies the optimal PUDO in a region that minimizes:

$$minF\left(d^a, d^{dr}, t^w{}_{d^a,d^{dr}}\right) = min \sum_{i\in I}\sum_{j\in P_i}\left[{d^a_{ji}}/_{S^w} + {d^{dr}_{is_i}}/_{S^{dr}} + t^w_j\left(d^a_{ji}, d^{dr}_{oi}\right)\right] \qquad (1)$$

s.t.

$$x_i \in V(x_i)$$

Where I is the set of PUDOs, and P_i is the set of demand points assigned to each meeting point i within the Voronoi cell. d^a_{ij} is the walking distance from demand point j to meeting point i, and $d^{dr}_{is_i}$ is the driving (Manhattan) distance from meeting point i to its closest BART station, s_i. $t^w_j\left(d^a_{ji}, d^{dr}_{oi}\right)$ is the waiting time of demand j, as a function of the maximum time passenger j has to wait, the time the driver takes to get to the meeting point, and the time the user may have to wait for the other users to arrive to the meeting point. Eq. 1 assumes vehicles located between the PUDO and the station. The optimization used an average driving speed of 20 miles/hour, and average walking speed of 4 feet/second.

In this project, the team refined, and conducted additional analyses to improve the Voronoi-based solution procedure. FIGURE 3 shows the different steps and component of the solution algorithm.

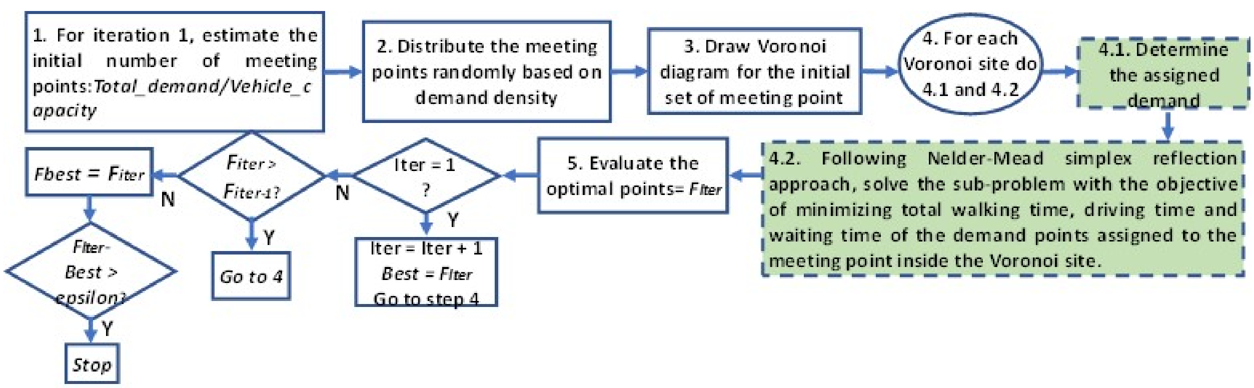


FIGURE 3 Optimization solution algorithm

Specifically, in this project, the team evaluated different assumptions about the demand. For instance, MTC-ABM provides the number of trips for the different simulation periods in a per hour basis. The team conducted analyses to discretize the demand in 15-minute intervals. Moreover, for the selection of the number and location of the meeting points, the team updated the initial method that creates a grid of equally sized cells to cover the study region. For instance, the size of the cells could be a function of the relationship between the areas of study region, estimated the number of meeting points to allocate to each cell based on its demand density, and randomly distributed the meeting throughout the cell. In this iteration, the team used the road network information, to locate the demand points, and conducted different procedures for the spatial distribution.

The team also conducted post-processing of the results to determine the solutions that could not be feasible based on the resulting distances and times. The team did not include these as constraints in the model to evaluate the entire set of demand points, and be able to analyze the need for additional policies or strategies to foster service participation.

Agent-based Analysis using MATSIM Model

The team uses the multi-agent transportation simulation (MATSIM) software to explicitly model the movement of individuals and vehicles in the network inside the study area. The simulation requires network attributes and the travelers' destination, times and mode choices. FIGURE 4 shows a general description of the simulation process (see Horni et al. (2016) for a detailed description of MATSIM). More importantly, there are a number of models available for this open software tool. One of them, the "Demand Responsive Transport (DRT)" is able to simulate a dynamic shared taxi service with online requests. This module handles vehicle dispatching for the supply side, and evaluates waiting times, trip and total detour lengths, and other characteristics of the problem (Bischoff et al., 2017b). The research team conducted simulations for the base case where an individual uses the private vehicle and the ridesharing+transit service described before.

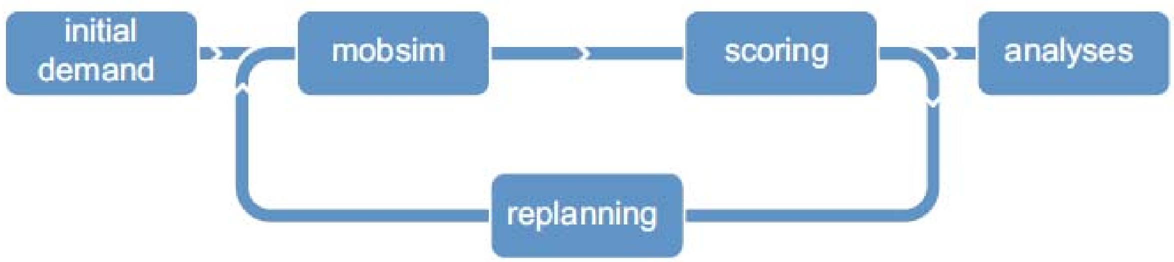


FIGURE 4 MATSIM loop (Horni et al., 2016)

Assessing Health Impacts

The team uses the Integrated and Health Impacts Model (ITHIM) to estimate system-level health effects (Mueller et al., 2015). ITHIM integrates the impacts of physical activity from active travel, road traffic injuries and fine particulate pollution. Specifically, ITHIM evaluates the changes in the population disease burden between evaluated scenarios. Woodcock et al. (2009); Maizlish et al. (2013); Woodcock et al. (2013); Whitfield et al. (2017) discuss the details of the open-source tool. The tool incorporates several important aspects (see FIGURE 5 for a general representation of the various components):

- Population attributable fraction (FAF): used in public health to refer to the percent of disease or injury avoided or reduced when eliminating a risk factor;
  - Risk factors–physical activity, fine particulate matter (PM2.5), road traffic injuries – and the health outcomes for specific causes, and
  - Exposure distribution of the risk factor.
- Disease burden (BD) from shift in the distribution of exposure in comparative scenarios (Ezzati et al., 2004). The change in DB is calculated by Eq. 2[2];

[2] The relative risk, RR, at exposure level (x) is weighted by the baseline and alternative population distributions, P(x) and Q(x), respectively, and summed over all exposure levels.

$$\Delta DB = \frac{\int_{X_{min}}^{X_{max}} RR(xx)P(x)dx - \int_{X_{min}}^{X_{max}} RR(xx)Q(x)dx}{\int_{X_{min}}^{X_{max}} RR(xx)P(x)dx} DB_{Baseline} \qquad (2)$$

- Relative risk (RR) –at exposure level x;
- Population burden expresses in deaths and disability adjusted life years (DALYs);
- DALY: years of living with disability;
- Chronic diseases include cardiovascular diseases (ischemic heart disease, hypertensive heart disease, and cerebrovascular disease), colon cancer, breast cancer, diabetes, depression, and dementia;
- Physical activity measured in metabolic equivalent task (MET) hours (Shephard, 2011);
- METs reflect energy expenditures for walking and bicycling at average speeds and for leisure activities and occupational tasks;
- Distance-based traffic injury model (Elvik and Bjørnskau, 2017);
- Automobile emissions based on vehicle miles traveled;
- Population-weighted average air pollutant concentrations; and
- Costs of illness and value of statistical life (Haddix et al., 2003; Maizlish and Siegel, 2012);
    - Cost of illness (COI),
    - Willingness to pay.

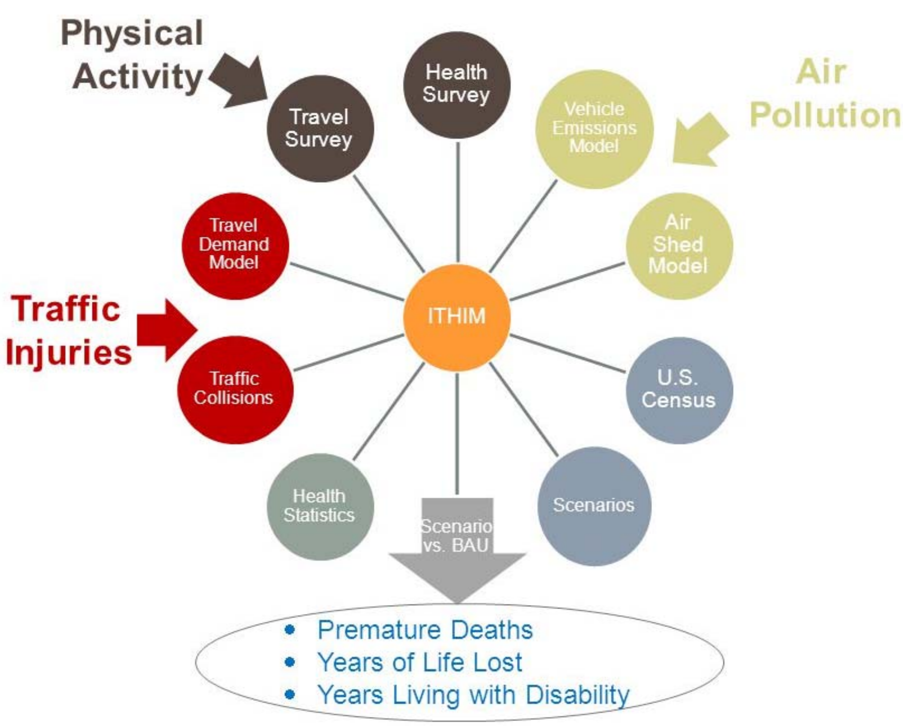


FIGURE 5 ITHIM considerations from Maizlish (2016)

ITHIM uses the literature and travel survey data to estimate the effects from physical activity for different types of populations, an air shed model for the air pollution concentrations, and uses EMFAC in California to estimate the emission factors per vehicle type. The team used the

California version of ITHIM, which has been successfully implemented in the San Francisco Bay Area, as well as other locations in Nevada, Southern California, Tennessee and Oregon. FIGURE 6 shows a representation of the modeling process. In this project, the team is using the results from the MTC simulations to feed as inputs of the ITHIM model. In the ongoing Year 3 project, the team is working on developing a more robust integration with the activity-based model and ITHIM.

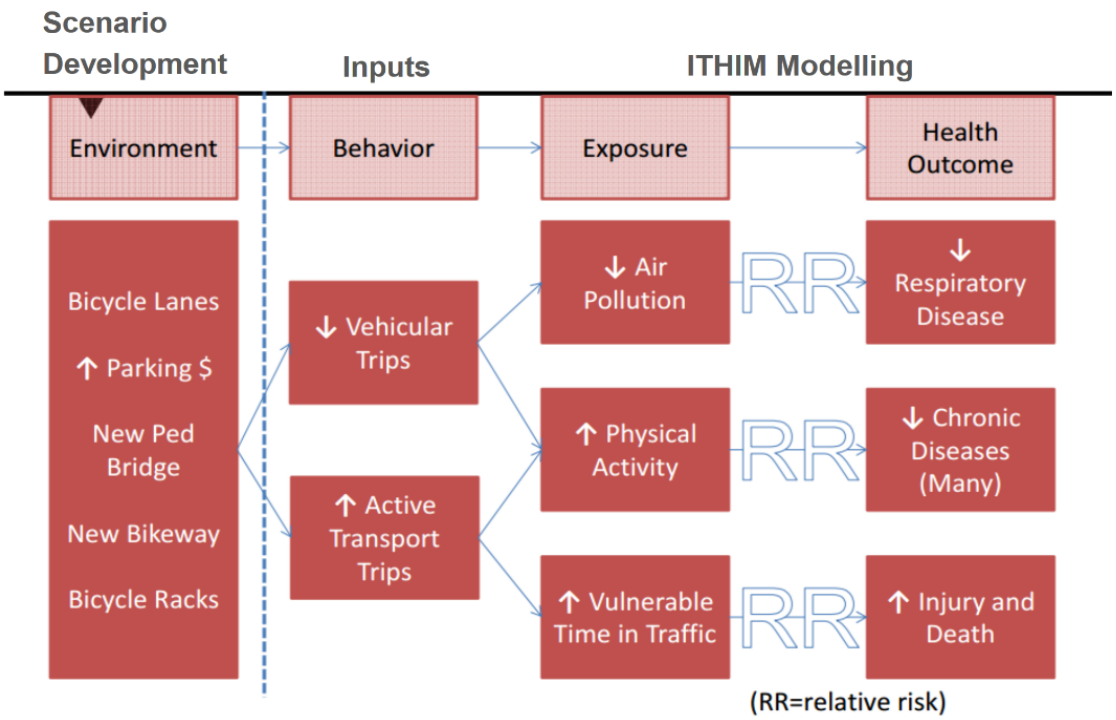


FIGURE 6 Scenario development (Center for Health Impact Evaluation, 2018)

Empirical Analyses

As mentioned before, the team developed a number of scenarios to evaluate the impacts in the Bay Area. The team followed the parameter changes in FIGURE 2, and developed the following scenarios in addition to the baseline (2010):

- R+T_AAO: Ridesharing+transit with age and auto ownership relaxation
- R+T_10AT: 90% reduction in access time
- R+T_50AT: 50% reduction in access time
- R+T_75AT: 25% reduction in access time
- R+T_50CPM: 50% reduction in cost per mile
- R+T_150CPM: 50% increase in cost per mile
- R+T_200CPM: 100% increase in cost per mile

Moreover, the team focused the analyses on work, shopping, and all trips for different time periods (EA, AM, MD, PM, and EV), and implemented the various framework components to a sub-set of these scenarios based on the preliminary findings. TABLE 1 summarizes the type of scenarios evaluated through the different components.

TABLE 1 Evaluated scenarios

Considered Trips	MTC-ABM	Optimization	MATSIM	ITHIM
All	All time periods Baseline R+T_10AT			
Work	For AM Peak Baseline R+T_10AT R+T_50AT R+T_75AT R+T_50CPM R+T_150CPM R+T_200CPM	For AM Peak Baseline R+T_10AT[3] R+T_75AT[4]	For AM Peak Baseline R+T_10AT[5] R+T_25AT	R+T_10AT[6]
Shopping	For Midday Baseline R+T_75AT			All day: Baseline R+T_75AT
Work + Shopping	For Midday Baseline R+T_75AT			All day: Baseline R+T_75AT

All Trips

The team estimated the impact on all trips for all simulation time periods for each of the modes assuming a reduction of 90% in access time to the “Drive_to_Heavy_Rail” mode.

TABLE 2 shows that the perception of reduced access time (individuals do not have to drive, park, and walk to the station) shifts demand from other modes to the ridesharing+transit service. Drive alone includes both toll and free roads, shared ride includes 2+ and 3+ private vehicle passengers, "Walk Transit" includes local buses, light rail or ferry, BART, express bus, and commuter rail, and drive transit includes local bus, light rail or ferry, express bus, and commuter rail. The team only modified the "Drive_to_ Heavy_Rail" as it included BARD. Almost 29,000 trips would shift, generating an increase demand ranging between 14% and 31% to BART. The results show a decrease in drive alone trips (except in the early morning period), with the AM, MD, PM, and EV periods reducing 11,962, 9,027, 6,635 and 9,741 trips respectively. However, because of the number of total trips, these reductions only represent between .2% and .53%. However, accessibility improvements to this mode have an impact on the number of walk_to_transit trips, reducing in the range of 0% to 3.3%, and in the drive to other transit between 6% and 13.53%.

TABLE 2 R+T_10AT scenario for all trips, modes and simulation time periods

Time Period	Scenario	Drive alone	Shared ride	Walk transit	Drive transit	Drive BART	Total
EA	Base	277,368	93,598	14,327	2,653	8,766	396,712
	R+T_10AT	278,052	94,110	13,855	2,294	11,072	399,383
	Diff	684	512	(472)	(359)	2,306	2,671
	Diff%	0.25	0.55	-3.29	-13.53	26.31	0.67
AM	Base	2,755,806	2,308,423	289,985	36,112	73,791	5,464,117
	R+T_10AT	2,743,844	2,304,973	285,450	31,836	96,576	5,462,679
	Diff	(11,962)	(3,450)	(4,535)	(4,276)	22,785	(1,438)
	Diff%	-0.434	-0.149	-1.564	-11.841	30.878	-0.026
MD	Base	3,244,399	2,465,274	159,580	4,903	8,955	5,883,111
	R+T_10AT	3,235,372	2,471,520	159,512	4,462	11,254	5,882,120
	Diff	(9,027)	6,246	(68)	(441)	2,299	(991)
	Diff%	-0.28	0.25	-0.04	-8.99	25.67	-0.02
PM	Base	3,513,735	2,646,915	304,127	3,415	4,579	6,472,771
	R+T_10AT	3,507,100	2,648,417	300,117	3,197	5,259	6,464,090
	Diff	(6,635)	1,502	(4,010)	(218)	680	(8,681)
	Diff%	-0.19	0.06	-1.32	-6.38	14.85	-0.13
EV	Base	1,829,080	1,278,012	119,484	343	686	3,227,605
	R+T_10AT	1,819,339	1,275,193	118,099	347	782	3,213,760
	Diff	(9,741)	(2,819)	(1,385)	4	96	(13,845)
	Diff%	-0.53	-0.22	-1.16	1.17	13.99	-0.43

These are interesting results as they show that even with significant reductions in access time (drive time to BART), individuals are not as sensitive to switch from drive alone. Moreover, as the remainder of the analyses focus on a sub-set of trip purposes, the expected results would be lower in magnitude. There are an estimated 21,4 million trips generated in one day in the Bay Area, about 95% are either driving alone or are passengers in private vehicles, and only .5% to 1.5% use BART. The drive to BART mode only includes a portion of the BART trips, as many other trips access the station by walking; the reported BART daily users in 2010 were around 350,000.

Work Trips

TABLE 3 shows the results for all the different scenarios (changes in access time and cost per mile) for the AM period. The 25% access time reduction (R+T_75AT) scenario shows that the number of BART users increase by almost 9% or 5,792 new trips. In total, this scenario reduces the number of drive alone trips in about 3,800, and about a quarter of those (1,007) are switching to BART. The results for the optimistic scenario of 90% reduction in access time (R+T_10AT) show a 35% increase in BART trips. For the total BART trips, the results show that 74% were already users, 4% or 3,341 shifted from drive alone, 6% from private vehicle passengers, and 14% from other transit.

TABLE 3 Mode share for work trips in the AM period for different scenarios

Scenario	Drive alone	Shared ride	Walk transit	Drive transit	Drive BART	Total
Base	1,081,554	222,579	140,871	30,203	65,013	1,540,220
R+T_AAO	1,081,429	222,729	140,851	30,151	64,945	1,540,105
Diff	(125)	150	(20)	(52)	(68)	(115)
% Diff	**-0.01**	**0.07**	**-0.01**	**-0.17**	**-0.10**	**-0.01**
Base	1,078,735	222,306	142,024	31,055	66,660	1,540,780
R+T_10AT	1,069,351	218,916	139,075	26,423	89,528	1,543,293
Diff	(9,384)	(3,390)	(2,949)	(4,632)	22,868	2,513
% Diff	**-0.87**	**-1.52**	**-2.08**	**-14.92**	**34.31**	**0.16**
Base	1,081,586	222,557	140,850	30,224	65,014	1,540,231
R+T_50AT	1,077,611	221,023	139,183	27,957	76,056	1,541,830
Diff	(3,975)	(1,534)	(1,667)	(2,267)	11,042	1,599
% Diff	**-0.37**	**-0.69**	**-1.18**	**-7.50**	**16.98**	**0.10**
Base	1,078,536	222,118	142,128	31,131	66,612	1,540,525
R+T_75AT	1,074,737	221,231	141,359	30,228	72,404	1,539,959
Diff	(3,799)	(887)	(769)	(903)	5,792	(566)
% Diff	**-0.35**	**-0.40**	**-0.54**	**-2.90**	**8.70**	**-0.04**
Base	1,078,575	222,114	141,857	31,035	66,621	1,540,202
R+T_50CPM	1,075,731	221,401	141,343	29,683	72,230	1,540,388
Diff	(2,844)	(713)	(514)	(1,352)	5,609	186
% Diff	**-0.26**	**-0.32**	**-0.36**	**-4.36**	**8.42**	**0.01**
Base	1,078,036	222,208	142,215	31,227	65,906	1,539,592
R+T_150CPM	1,078,603	223,310	143,049	32,160	61,918	1,539,040
Diff	567	1,102	834	933	(3,988)	(552)
% Diff	**0.05**	**0.50**	**0.59**	**2.99**	**-6.05**	**-0.04**
Base	1,077,636	222,316	142,127	31,351	66,812	1,540,242
R+T_200CPM	1,078,565	223,970	143,887	33,391	58,122	1,537,935
Diff	929	1,654	1,760	2,040	(8,690)	(2,307)
% Diff	**0.09**	**0.74**	**1.24**	**6.51**	**-13.01**	**-0.15**

FIGURE 7 and FIGURE 8 show the number of trips switching from drive alone to the service, and the average change in trip times. The figures show that the simulated users are not as sensitive to changes in cost (both scenarios include age and auto ownership relaxations)

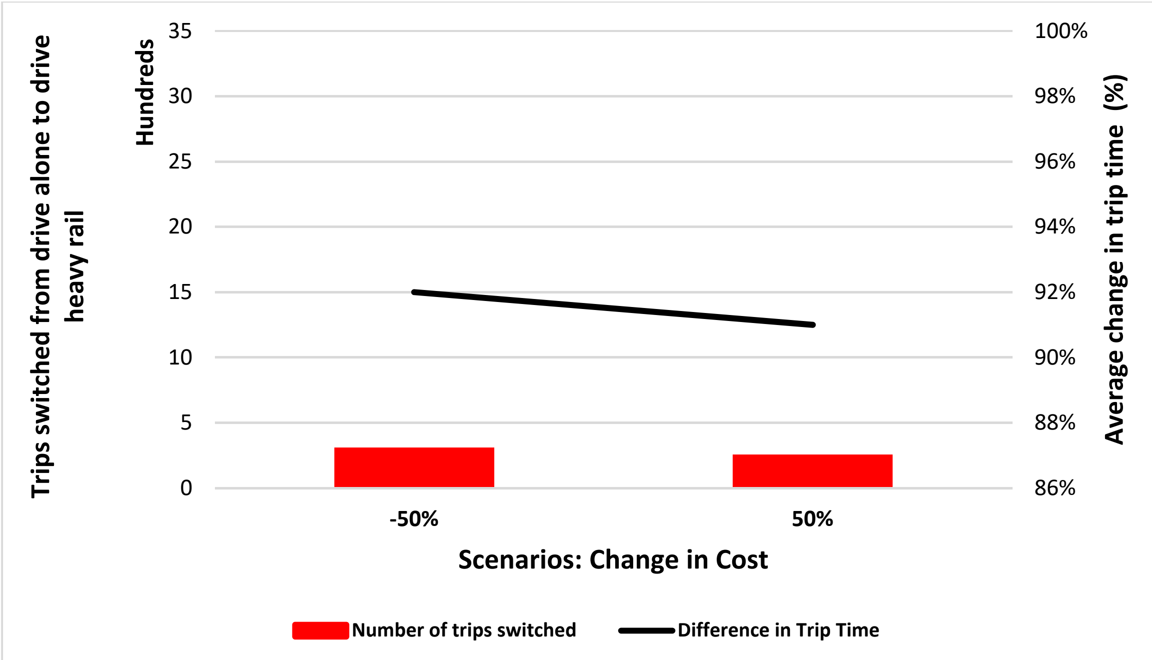


FIGURE 7 Average changes in trip time and trips switched from drive alone for cost scenarios

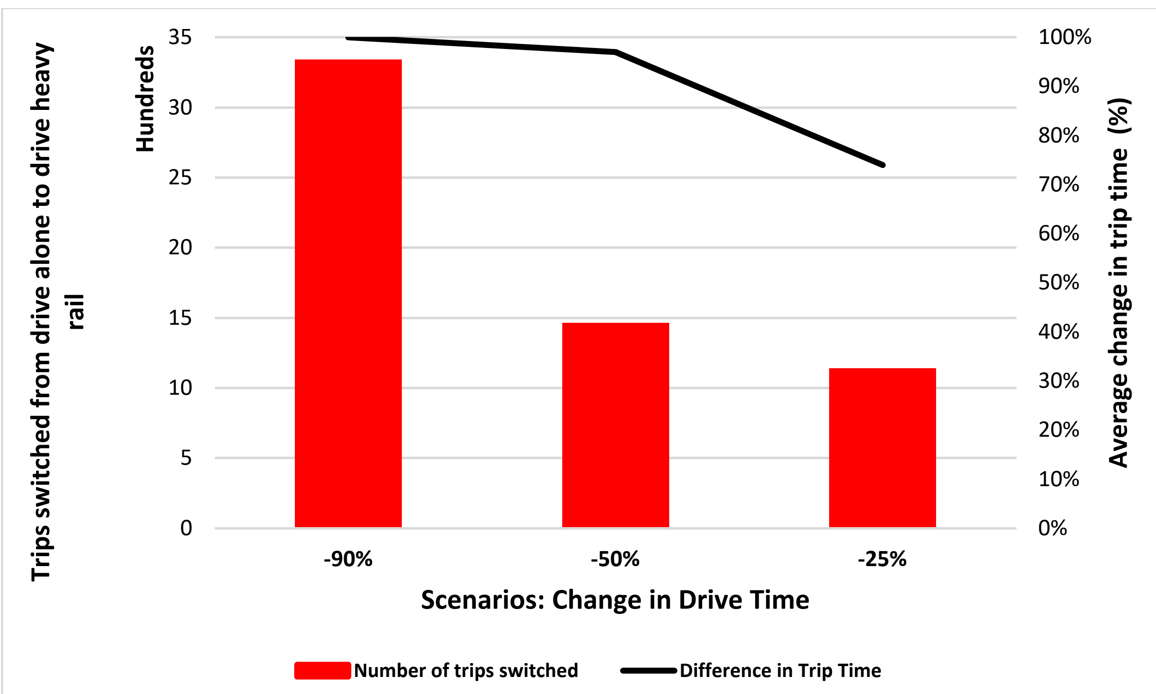


FIGURE 8 Average changes in trip time and trips switched from drive alone for access time scenarios

R+T_10AT

For the R+T_10AT scenarios, the team identified the information (characteristics and trips), for those individuals that shifted from drive alone. The team used these individuals as the input of the location-allocation algorithm to find the PUDOs. The model resulted in around 400 common locations for the 3,341 individuals. There could be more than one PUDO at each of these locations, determined by the number of individuals assigned to the location, and the vehicles capacity. For the case where the vehicle originates at the station, TABLE 4 shows the average, maximum and minimum times for walking, waiting, and driving times. FIGURE 9 shows the average times for the cases where the vehicles is at the PUDO, at the station, or between the point and the station. The results only include the drive time of users from the PUDO to the station, and not the drive time of the empty vehicle. For the vehicle at the point, there is still waiting times, associated to the individuals that have to walk to the PUDO. However, compared to the case where the vehicle is at the station, the time decreases from almost 20 minutes to 4, when the vehicle is ready, or even half when the vehicle is at the midpoint.

TABLE 4 Walk time, wait time and drive time when vehicle at the station

	Walking Time (minute)	**Waiting Time (minute)**	**Driving Time (minute)**
Average	17	20	30
Maximum	72	88	90
Minimum	1	0	1

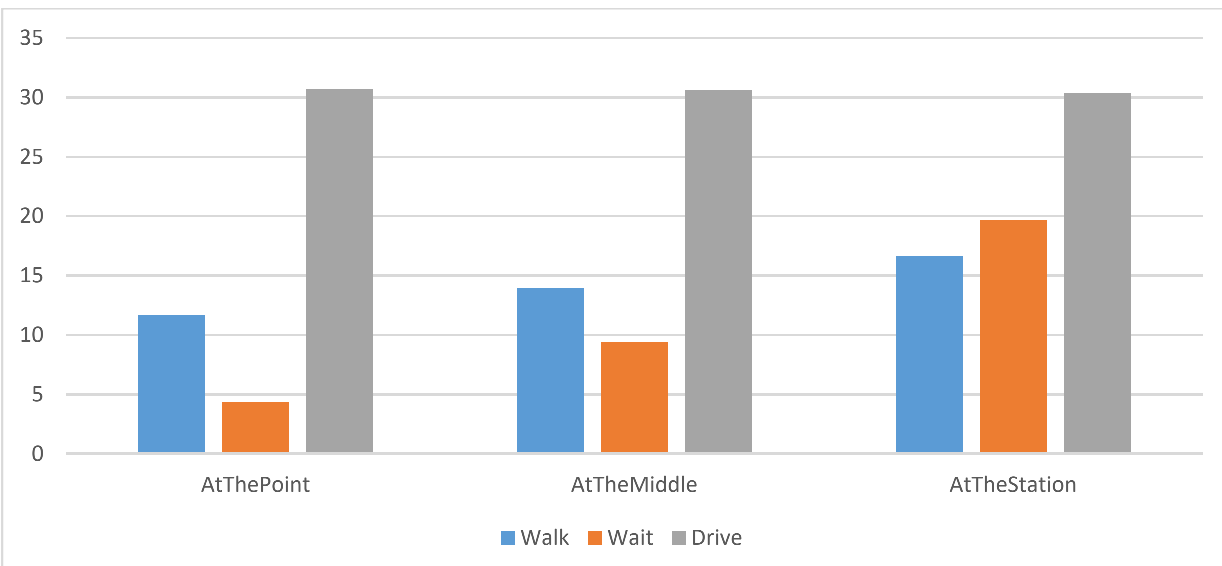
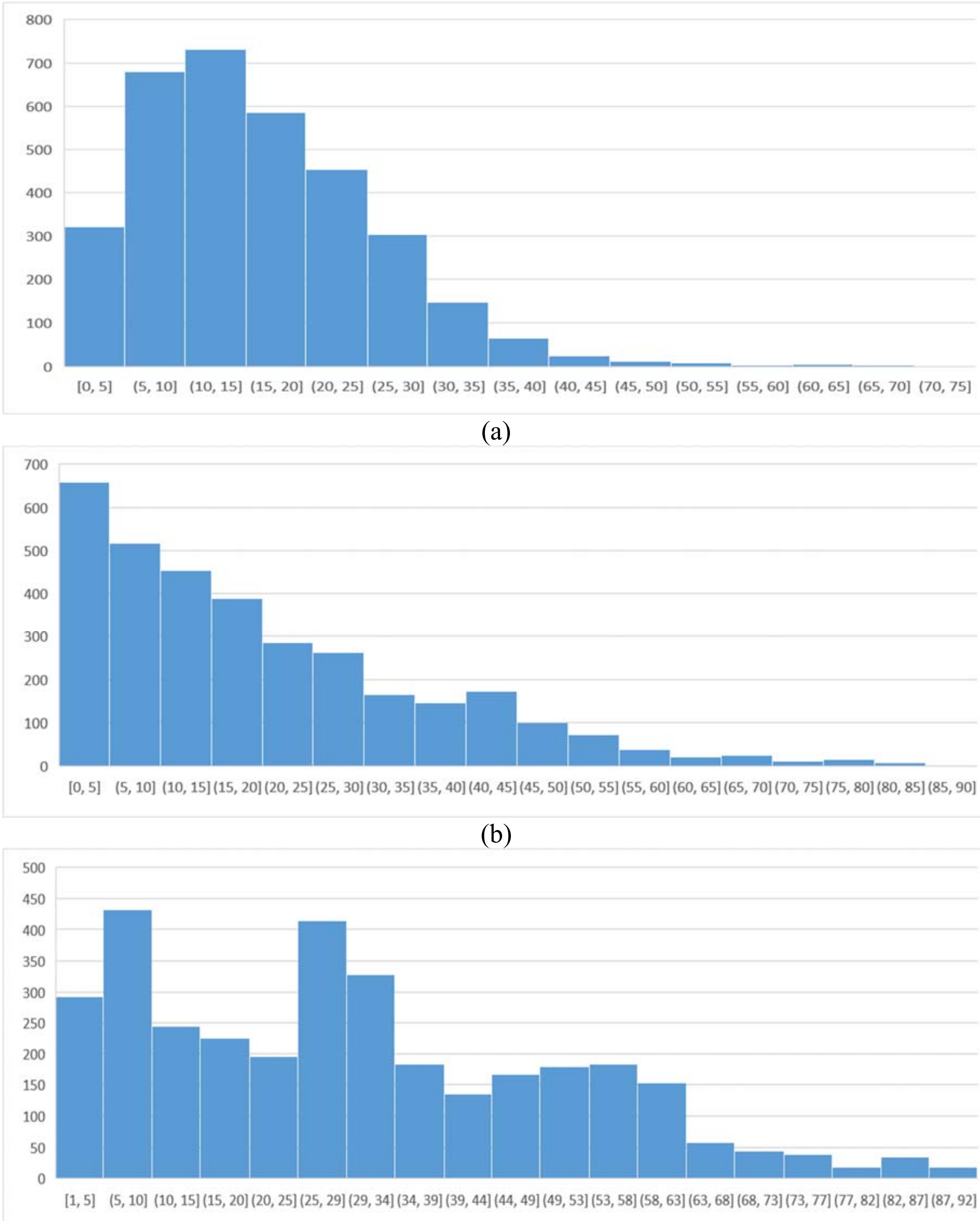


FIGURE 9 Comparative results for different assumptions about vehicle initial location

FIGURE 10 provides additional details on the frequencies for these times considering all the meeting points. The results clearly show that if users have perceived thresholds for walking, waiting, and drive times, there would be a significant number of them that will not use the service. Although, the graphs do not indicate the relationship between the three estimated times for the same users. Assuming a maximum of 10 minutes for waiting and walking times, there would be still about a third of the shifting users that would be able to use it.



(c)

FIGURE 10 Frequency distribution of (a) Walk Time (minute), (b) Wait Time (minute) and (c) Drive Time (minute)

The authors used the trip data from MTC-ABM and the PUDO locations from the optimization to conduct the agent-based simulations. For the simulations, the authors used the information of all travelers using the driver to BART mode. The authors considered three different scenarios in the MATSIM simulation (see TABLE 5) and compared the results to a base case where each individual would drive alone. The simulation does not consider parking cost or capacity constraints. The simulations assume that when multiple users, the per mile cost drops to half for each user; however, the simulations do not consider a time-based cost.

TABLE 5 Operating cost

Scenario	Vehicle	Paying Occupants	Pick-Up Location	Costs
Base Case	Personal	Single	Home	$0.18 per mile
Scenario 1	Shared Ride	Single	Home	$1.50 per mile
Scenario 2	Shared Ride	Multiple	Home	$0.75 per mile
Scenario 3	Shared Ride	Multiple	Meeting Point	$0.75 per mile

TABLE 6 shows the results for the different scenarios. Scenario 1 shows that only 12% of users would benefit from using the ridesharing service with an average cost saving of $1.24 per trip. Scenario 2 improves the cost performance by saving generalized cost for 33% of the trips (with the average benefit of $1.50 per trip). However, when instead of being picked-up at their origin (home) locations and they have to walk and wait at the PUDO (scenario 3), only 16% would benefit, reducing the potential demand by half.

TABLE 6 Change in generalized costs from the base case to the alternative scenarios during the AM peak period work trips

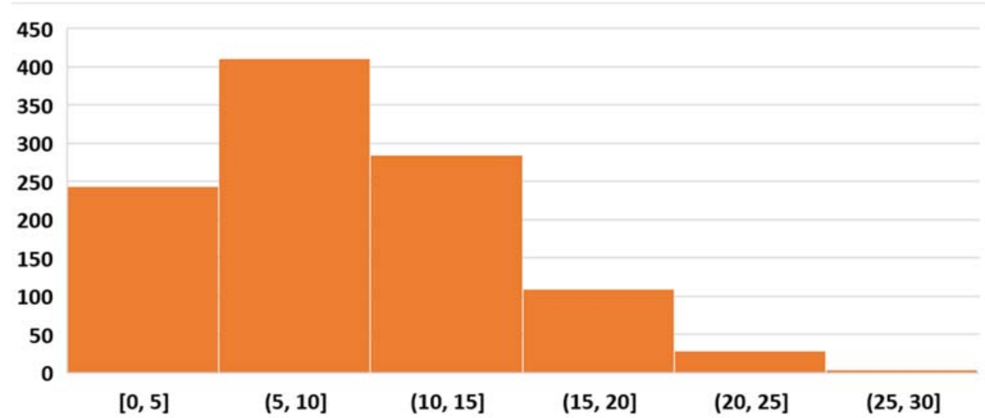
Generalized Cost: Change from Base Case	Scenario 1: Shared-Ride Home Pick-Up	Scenario 2: Shared-Vehicle Home Pick-Up	Scenario 3: Shared-Ride Meeting Pick-Up Point
Trips Gain%	12%	33%	16%
Average	$1.24	$1.52	$1.49
Total	$11,035.11	$38,979.15	$18,847.62
Trips Loss%	88%	67%	84%
Average	-$8.80	-$3.49	-$11.22
Total	-$599,922.76	-$179,529.53	-$722,632.90

These results are consistent with the findings from the optimization, which show that walking and waiting times could be very high. Consequently, the service would not be attractive to most of these users. The next results show the analyses for a lower assumption in terms of "perceived" access time reductions of only 25%.

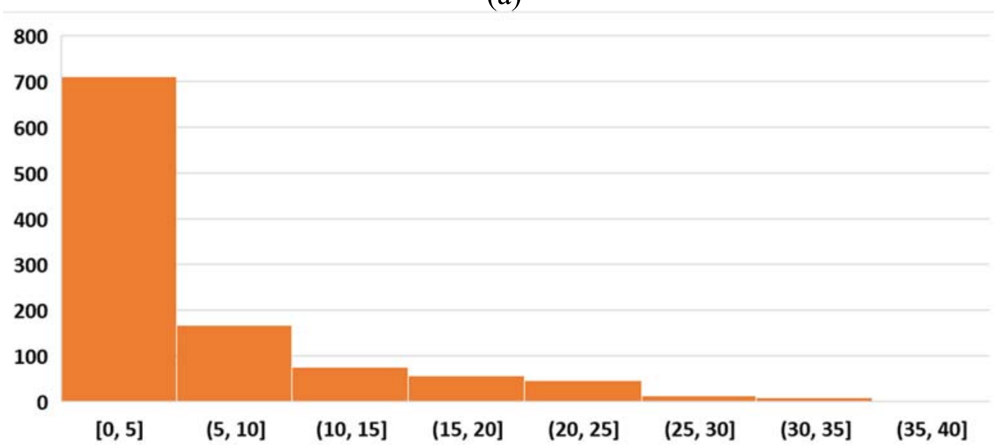
R+T_75AT

The authors implemented the optimization algorithm to find the optimal meeting points for the 1,077 individuals that "shifted" to the ridesharing+transit service. Each vehicle has a capacity of four and initiates its trip in middle between the meeting point and its closest BART station. The model estimated around 555 meeting points.

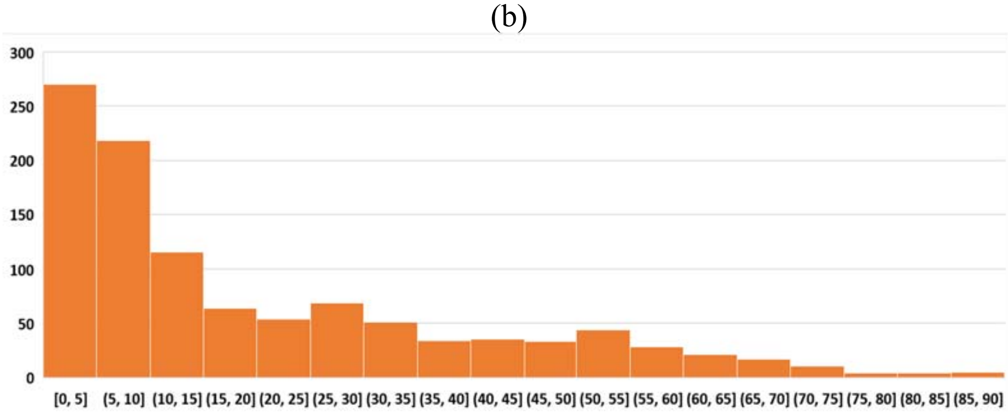
The results show that the average walking time to the stations is 17 min., average drive time is 20 min., and average waiting time is 7 min. On average, there are 2 travelers per meeting point. FIGURE 11 shows the distribution for walk time, drive time and wait time.



(a)



(b)



(c)

FIGURE 11 Frequency distribution of (a) Walk Time (minute), (b) Wait Time (minute) and (c) Drive Time (minute)

The results show that there is a large portion of individuals that could experience a combined waiting and walking time of more than 20 minutes, up to an hour (without considering the driving time from the meeting point to the station). However, around 30 to 40% of the travelers could be between 5 to 20 mins.

Similarly, the authors considered the 1,077 individuals in the MATSIM simulation scenarios. MATSIM simulates the individual's movement from origin to BART station comprised of walking and ridesharing. Time and cost of the rest of the trip from BART station to final work destination were estimated using BART API data. The authors simulated two scenarios, the base case and the ridesharing+transit service.

In the base scenario, all the individuals drive their own personal car as a single occupant from home to the final work destination. Time component consists of drive time from home to work plus zonal terminal time derived from MTC model demonstrating the average time to travel from automobile storage location to final destination. Costs include operating costs per mile (of 36 cents per mile according to the MTC model and zonal long term-8 hours- parking cost extracted from MTC model TAZ data). The general cost includes the time component multiplied by each individual's unique value of time (VOT) and the travel cost component.

In the ridesharing+transit scenario, all individuals walk from their home to their predetermined PUDO, and ride with possibly other individuals to the closest BART station. Then, take BART to the closest station to their work place, get off at the destination station and walk to the work place. The time components include walk time from home to work, wait time at the meeting point for the vehicle, travel time in shared vehicle, wait time for BART, BART travel duration and zonal terminal time from station to destination. The cost component comprises of rideshare service cost per mile (75 cents per mile per passenger representing the fare of services such as Uber in the Bay Area and BART fare). All the BART related parameters as travel duration, wait time and fare were derived from BART API online service between all stations across all time period. The general cost includes the time component multiplied by each individual's unique value of time (VOT) and the travel cost component.

This scenario assumed a vehicle fleet size of 1,080 cars. According to the waiting time and detour constraints within MATSIM's vehicle assignment algorithm, 66 trips were cancelled. As an assumption, users with cancelled pick-ups will use their private car to drive to work. The simulations show that the total distance traveled by the vehicles reduces from 24,607 miles to 7,750 in this scenario from the base case. About half (44%) of the distance (3,442) the vehicles are empty (just driver). Under this scenario the largest percentage of the trip uses BART. TABLE 7 shows the modeling results. The explicit simulation of the trips shows that, in average, the program increases the user's time in about 4 minutes, with an average total trip time of 91 mins. In terms of cost, 68% of the trips have saved cost by an average of $7 per trip, while the remaining 32% trips lost a total of $4,943. The total estimated general cost is $19,176 for 74% of trips which is far higher than the total saved amount of $1,426.

FIGURE 12 shows the distribution of travel duration (including wait time when appropriate) for all modes inside the simulated trips.[3] Walk times distribute within reasonable ranges (under 20 minutes) and overall individual trips' walk times have a high level of agreement with each other. On the other hand, BART travel time covers a longer range of values across individual trips with more trips having travel times longer than 30 minutes. The range of travel time for rideshare mode is slightly higher than BART mode with lower variations among different trips.

[3] Outliers are removed.

TABLE 7 Modeling results

Rideshare+Transit	Time: Change from Base Case	Cost: Change from Base Case	Generalized Cost: Change from Base Case
Trips Gain%	1%	68%	26%
Average	4 (min)	$7	$5
Total	8 (min)	$4,943	$1,426
Average	91 (min)	$5	$25

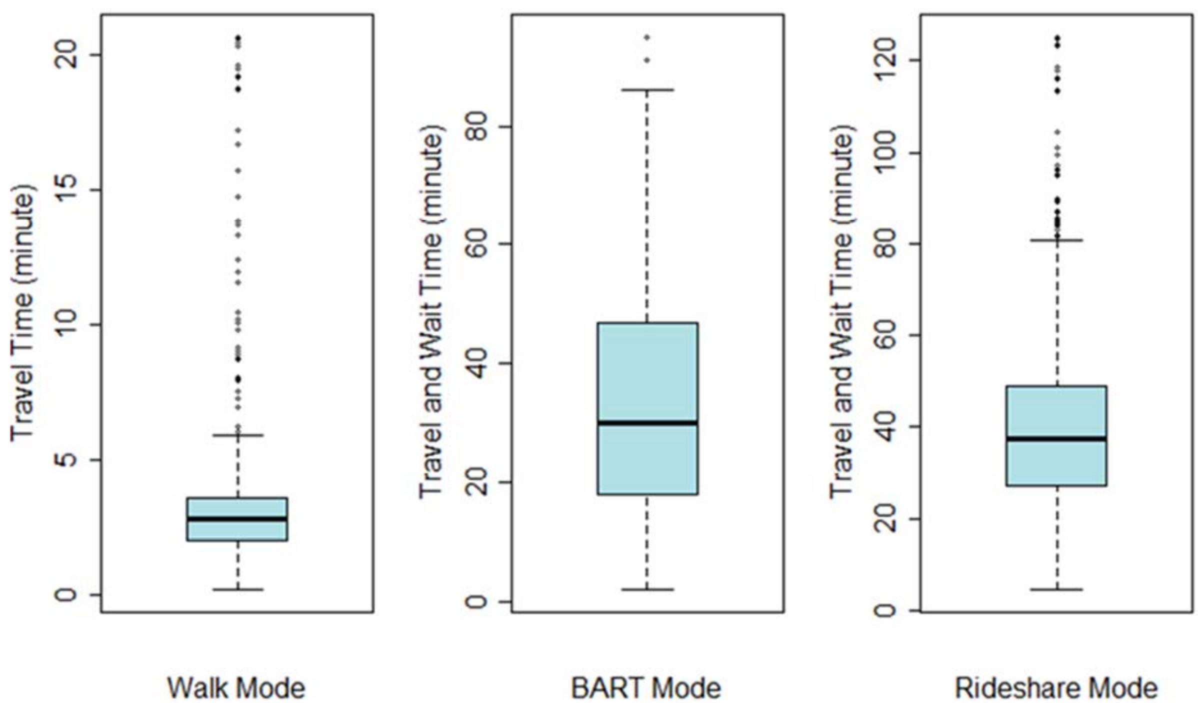


FIGURE 12 Travel time distribution for three simulated modes

FIGURE 13 displays the change in general cost from base to pool case for different categories of income. Individuals with higher level of income have higher range of increased generalized cost, while individuals in low-income groups have lower cost increases.

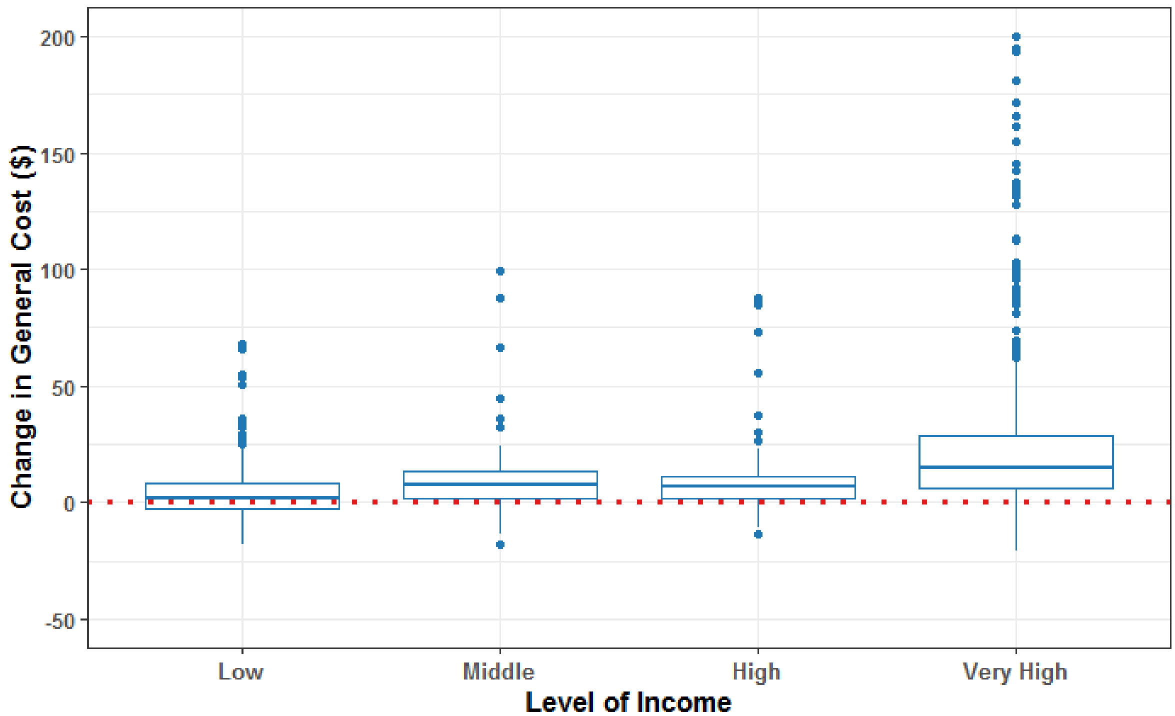


FIGURE 13 Changes in general cost from base to ridesharing+transit for various level of income

Shopping and Shopping + Work Trips

As mentioned in TABLE 1, the team conducted the analyses for shopping trips for the midday time period. This is because this period exhibits the largest number of trips with a shopping purpose. TABLE 8 compares the results for shopping trips between the base case and the R+T_75AT scenario. This effort generated mixed results. Shopping trips using transit do not account for a large number of daily trips (only 1.45%).

Although the number of drive_to_BART users is not significant, this scenario generated shifts between trips from the different modes. Overall, drive alone and passenger (shared) trips reduced in almost 2% each, walk to transit gained about 50%, while driving to transit increased by 30%. From the transit related modes, walk to transit gained the largest number of trips (around 8,000) during the day, while drive_to_BART less than 250.

Additionally, the team evaluated a combined scenario reducing the drive (access) time to BART (R+T_75AT) for both work and shopping trips during the midday period. TABLE 9 shows the results for this combined scenario. The top table shows the changes for shopping trips and the bottom for work trips. Consistent with the previous results, the net changes in shopping trips is very modest, while the results for work trips are more positive. One interesting finding from the results is that changes to the midday time period are larger during the AM and EA trips.

Nevertheless, compared to the total number of trips in a day, these changes are very small. Affecting the access time during the midday, only increases the total of drive_to_BART work trips in around 5,000 daily trips (from a total of 2.5 million).

TABLE 8 Results for shopping trips during midday for R+T_75AT

Time Period	Scenario	Drive alone	Shared ride	Walk/Bike	Walk transit	Drive transit	Drive BART	Total
EA	Base	5,239	2,273	619	91	-	8	8,230
	R+T_75AT	5,111	2,262	643	182	1	8	8,207
	Diff	(128)	(11)	24	91		0	(23)
	Diff%	-2.44%	-0.48%	3.88%	100.00%		0.00%	-0.28%
AM	Base	151,890	71,240	18,419	3,778	144	265	245,736
	R+T_75AT	147,631	71,883	17,912	5,409	166	313	243,314
	Diff	(4,259)	643	(507)	1,631	22	48	(2,422)
	Diff%	-2.80%	0.90%	-2.75%	43.17%	15.28%	18.11%	-0.99%
MD	Base	330,431	143,995	42,687	7,083	181	345	524,722
	R+T_75AT	326,316	147,376	41,682	9,813	230	428	525,845
	Diff	(4,115)	3,381	(1,005)	2,730	49	83	1,123
	Diff%	-1.25%	2.35%	-2.35%	38.54%	27.07%	24.06%	0.21%
PM	Base	209,598	96,348	25,408	4,186	104	187	335,831
	R+T_75AT	205,852	98,192	26,027	6,866	156	244	337,337
	Diff	(3,746)	1,844	619	2,680	52	57	1,506
	Diff%	-1.79%	1.91%	2.44%	64.02%	50.00%	30.48%	0.45%
EV	Base	42,775	17,901	4,745	709	15	31	66,176
	R+T_75AT	41,705	17,806	5,128	1,430	22	66	66,157
	Diff	(1,070)	(95)	383	721	7	35	(19)
	Diff%	-2.50%	-0.53%	8.07%	101.69%	46.67%	112.90%	-0.03%

Following, the team used the results from the shopping and shopping+work trip scenarios to estimate the health impacts using ITHIM. ITHIM estimates the impacts comparing the results to various baseline scenarios. The team used an ITHIM version calibrated to the MTC 2000 travel patterns, and the team also updated the parameters for the 2010 base case.

TABLE 10 shows the parameters (from MTC-ABM) for the various modes in the Bay Area simulation. These include average travel times, speeds, and distances per day. As mentioned before, the results from the simulation only show very small changes in the overall travel patterns which translate into very small impacts on times, distances and speeds.

Considering that ITHIM uses exposure, traffic incidents, and emission rates that are very small in a per mile basis, the small impacts of the scenarios did not show any significant health impacts in the study area (see TABLE 11).

TABLE 12 also show the results for the different diseases and injury changes as percentage for males and females for the entire population. As shown, the results do not generate any significant changes, just a small decrease in injuries.

TABLE 9 Results for midday for R+T_75AT combining shopping+work trips

	Time Period	Scenario	Drive alone	Shared ride	Walk/ Bike	Walk transit	Drive transit	Drive BART	Total
Shopping trips	EA	Base	5,111	2,262	643	182	1	8	8,207
		R+T_75AT	5,040	2,248	589	158	3	12	8,050
		Diff	(71)	(14)	(54)	(24)	2	4	(157)
		Diff%	-1.39%	-0.62%	-8.40%	-13.19%	200.00%	50.00%	-1.91%
	AM	Base	147,631	71,883	17,912	5,409	166	313	243,314
		R+T_75AT	148,044	71,844	17,851	5,393	181	324	243,637
		Diff	413	(39)	(61)	(16)	15	11	323
		Diff%	0.28%	-0.05%	-0.34%	-0.30%	9.04%	3.51%	0.13%
	MD	Base	326,316	147,376	41,682	9,813	230	428	525,845
		R+T_75AT	325,161	147,154	41,494	9,938	227	465	524,439
		Diff	(1,155)	(222)	(188)	125	(3)	37	(1,406)
		Diff%	-0.35%	-0.15%	-0.45%	1.27%	-1.30%	8.64%	-0.27%
	PM	Base	205,852	98,192	26,027	6,866	156	244	337,337
		R+T_75AT	205,543	97,894	26,083	6,852	144	319	336,835
		Diff	(309)	(298)	56	(14)	(12)	75	(502)
		Diff%	-0.15%	-0.30%	0.22%	-0.20%	-7.69%	30.74%	-0.15%
	EV	Base	41,705	17,806	5,128	1,430	22	66	66,157
		R+T_75AT	41,571	17,800	5,057	1,295	22	53	65,798
		Diff	(134)	(6)	(71)	(135)	0	(13)	(359)
		Diff%	-0.32%	-0.03%	-1.38%	-9.44%	0.00%	-19.70%	-0.54%
Work trips	EA	Base	152,831	62,731	9,387	11,783	1927	6788	245,447
		R+T_75AT	153,473	62,875	9,013	11,724	1743	6954	245,782
		Diff	642	144	(374)	(59)	(184)	166	335
		Diff%	0.42%	0.23%	-3.98%	-0.50%	-9.55%	2.45%	0.14%
	AM	Base	1,122,010	476,802	86,111	185,949	27391	68876	1,967,139
		R+T_75AT	1,121,203	476,433	85,774	184,034	25522	72818	1,965,784
		Diff	(807)	(369)	(337)	(1,915)	(1,869)	3,942	(1,355)
		Diff%	-0.07%	-0.08%	-0.39%	-1.03%	-6.82%	5.72%	-0.07%
	MD	Base	159,325	65,506	14,847	24,758	2782	7387	274,605
		R+T_75AT	159,272	65,931	15,214	25,082	2480	7671	275,650
		Diff	(53)	425	367	324	(302)	284	1,045
		Diff%	-0.03%	0.65%	2.47%	1.31%	-10.86%	3.84%	0.38%
	PM	Base	41,186	17,057	4,664	6,479	619	1526	71,531
		R+T_75AT	41,354	17,082	4,439	6,295	556	1719	71,445
		Diff	168	25	(225)	(184)	(63)	193	(86)
		Diff%	0.41%	0.15%	-4.82%	-2.84%	-10.18%	12.65%	-0.12%
	EV	Base	4,662	1,857	567	679	56	140	7,961
		R+T_75AT	4,614	1,894	559	702	46	146	7,961
		Diff	(48)	37	(8)	23	(10)	6	0
		Diff%	-1.03%	1.99%	-1.41%	3.39%	-17.86%	4.29%	0.00%

Moreover, FIGURE 14 shows the changes in disease and injury burden for all users. The positive values for the shopping+work trip scenario result from the mode shifts due to the reduction in perceived access time, which generates additional driving miles. These results do not include the changes in walking from the different service users when they need to walk to the PUDO because this is not captured by the MTC-ABM.

TABLE 10 ITHIM parameters

	Mode	Baseline2010		Shopping		Shopping and work	
Time (minutes per day)	walk	8.2	16%	8.2	17%	8.2	16%
	cycle	0.42	0.01	0.4	1%	0.4	1%
	bus	1.7	4%	1.7	4%	1.7	4%
	minibus						
	train	1.6	3%	1.6	3%	1.6	3%
	car driver	28.4	57%	28.4	57%	28.4	57%
	car passenger	9.1	18%	9.1	18%	9.1	18%
	mbike	0.3	1%	0.0	0%	0.0	0%
	total	49.7	100%	49.5	100%	49.5	100%
Mean speed (mph)	walk	3.0		3.0		3.0	
	cycle	12.0		12.0		12.0	
	bus	9.0		9.0		9.2	
	minibus						
	train	25.3		25.3		25.9	
	car driver	32.4		32.4		32.4	
	car passenger	31.1		31.1		31.2	
	mbike	32.4		32.4		32.4	
Distance (mile per day)	walk	0.41	2%	0.4	2%	0.4	2%
	cycle	0.08	0%	0.1	0%	0.1	0%
	bus	0.3	1%	0.3	1%	0.3	1%
	minibus						
	train	0.7	3%	0.7	3%	0.7	3%
	car driver	15.3	65%	15.3	65%	15.4	65%
	car passenger	4.7	20%	4.7	20%	4.8	20%
	mbike	0.1	1%	0.1	1%	0.1	1%
	truck	1.9		1.8		1.8	
	total	23.5	100%	23.4	92%	23.5	92%
Total Population		**7,351,177**					
Coefficient of var		1.65		1.65		1.65	

TABLE 11 ITHIM summary results for different scenarios

Scenario Name	Baseline2010	BAU2040		Shopping		Shopping and work	
Year	2010	2010		2010		2010	
Population	7,053,334	7,351,177		7,053,334		7,053,334	
Car VMT/y (1,000s)	39,476,408	41,778,999		39,469,660		39,544,480	
CO_2 lbs./mile*	0.89776	0.89776		0.89776		0.89776	
	Value	Value	%	Value	%	Value	%
Aggregate CO2 (MMT/y)	16.1	17.0	5.59	16.1	0	16.1	0
Per Capita CO2 (MT/person/yr)	2.3	2.3	0	2.3	0	2.3	0
Mean $PM_{2.5}$ ($\mu g/m^3$)	9.3			9.3	0	9.3	0

TABLE 12 Results for health impacts from shopping (top) and shopping+work (bottom) scenarios

	Breast Cancer		Colon Cancer		Ischemic Heart Disease		Depression		Dementia		Diabetes		Stroke		Road Traffic Injuries		All-cause mortality Woodcock	
Age	m	f	m	f	m	f	m	f	m	f	m	f	m	f	m	f	m	f
15-29	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-0.01	-0.01	0%	0%
30-44	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-0.01	-0.01	0%	0%
45-59	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-0.01	-0.01	0%	0%
60-69	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-0.01	-0.01	0%	0%
70-79	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-0.01	-0.01	0%	0%
80+	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-0.01	-0.01	0%	0%
total	0%		0%		0%		0%		0%		0%		0%		-1%		0%	

	Breast Cancer		Colon Cancer		Ischemic Heart Disease		Depression		Dementia		Diabetes		Stroke		Road Traffic Injuries		All-cause mortality Woodcock	
Age	m	f	m	f	m	f	m	f	m	f	m	f	m	f	m	f	m	f
15-29	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0.00	0.00	0%	0%
30-44	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0.00	0.00	0%	0%
45-59	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0.00	0.00	0%	0%
60-69	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0.00	0.00	0%	0%
70-79	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0.00	0.00	0%	0%
80+	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0.00	0.00	0%	0%
total	0%		0%		0%		0%		0%		0%		0%		0%		0%	

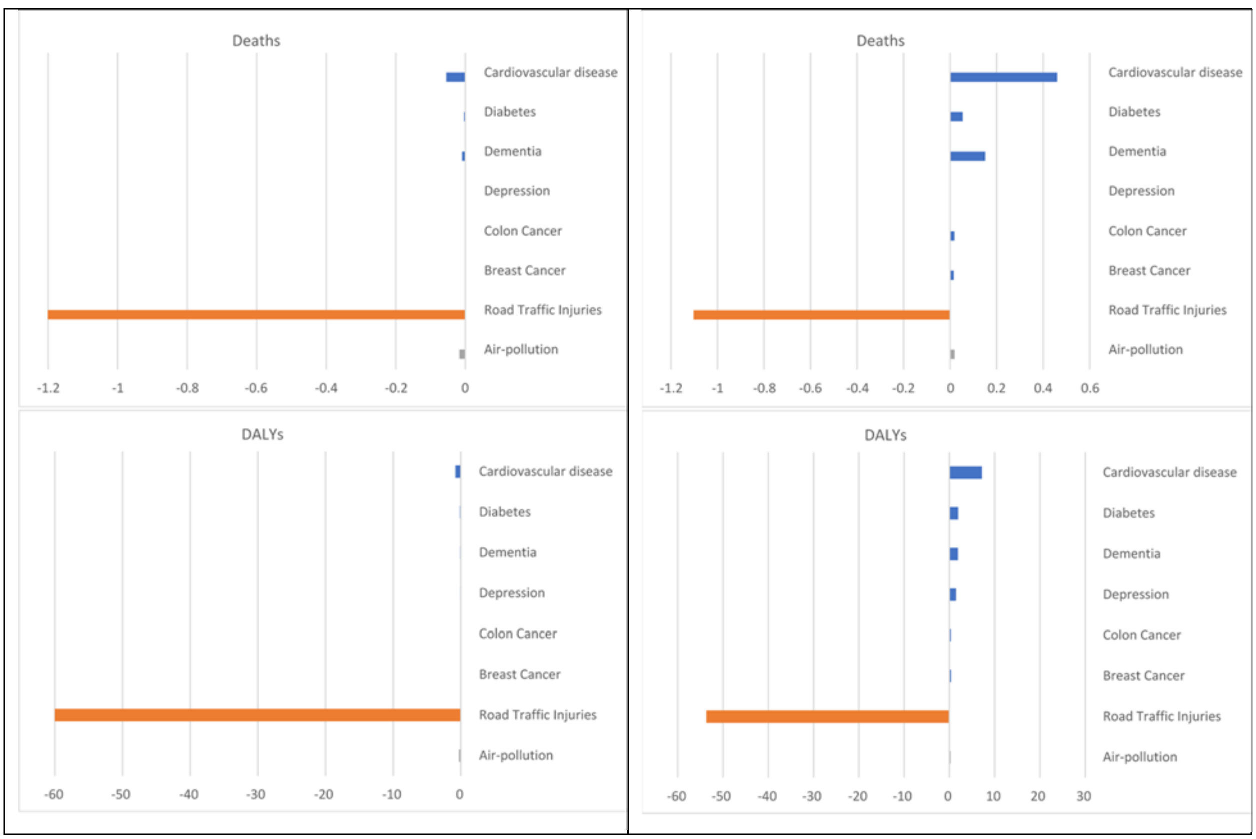


FIGURE 14 Change in disease and injury burden from shopping (left) and shopping+work scenarios (right)

To understand the potential health impacts, the team analyzed the results for the work trip scenario under R+T_10AT (which reduces the perceived drive time by 90%). In this scenario, 3,341 individuals switched from drive alone to the service. The team used the information for these individuals to estimate their impacts. The authors assumed that these individuals would considerably reduce their drive distance and times, and increase walking. That is, their new driving distances would relate to the driving from PUDO to the BART station, and the walking would increase with the distance and time to reach the PUDO. While this is not the complete information about those individuals' daily activity, it can provide an indication of the health impacts associated to their mode shift for this scenario.

TABLE 13 and FIGURE 15 show the results for the 3,341 individuals (assuming population's demographic characteristics). The results show that the disease burden would reduce between 2 and 8%, and the road injuries by more than 10%. FIGURE 15 shows the expected decrease in DALYs per individual. While, the numbers for the entire bay area mask these results, there are health benefits by increase active travel for the shifting individuals. Nevertheless, every system user has different levels of exposure.

TABLE 13 Results for health impacts for work AM trips (R+T_10AT)

	Breast Cancer		Colon Cancer		Ischemic Heart Disease		Depression		Dementia		Diabetes		Stroke		Road Traffic Injuries		All-cause mortality Woodcock	
Age	m	f	m	f	m	f	m	f	m	f	m	f	m	f	m	f	m	f
15-29	0%	-1%	-1%	-1%	-8%	-9%	-1%	-1%	-2%	-3%	-7%	-8%	-8%	-9%	-11%	-11%	-1%	-1%
30-44	0%	-2%	-2%	-2%	-9%	-9%	-2%	-3%	-2%	-3%	-8%	-8%	-9%	-9%	-11%	-11%	-1%	-1%
45-59	0%	-1%	-2%	-1%	-9%	-8%	-2%	-2%	-3%	-2%	-8%	-8%	-9%	-8%	-11%	-11%	-1%	-1%
60-69	0%	-2%	-2%	-2%	-9%	-9%	-2%	-3%	-3%	-4%	-8%	-8%	-9%	-9%	-11%	-11%	-1%	-2%
70-79	0%	-2%	-2%	-2%	-7%	-8%	-2%	-4%	-3%	-5%	-6%	-8%	-7%	-8%	-11%	-11%	-2%	-3%
80+	0%	-3%	-3%	-3%	-8%	-6%	-3%	-5%	-4%	-6%	-7%	-5%	-8%	-6%	-11%	-11%	-2%	-5%
total	-2%		-2%		-8%		-2%		-5%		-8%		-8%		-11%		-2%	

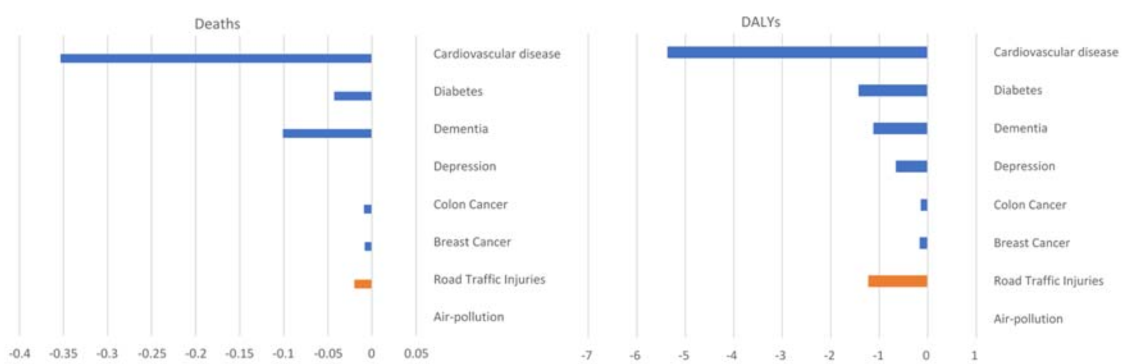


FIGURE 15 Change in disease and injury burden for work AM trips (R+T_10AT)

Discussion and Conclusions

This study evaluated a first mile transit access program using ridesharing. Specifically, the program allocates travel demand to pick-up and drop-off locations (PUDOs) where users access by walking, then ridesharing vehicles drive them to the closest BART station. The authors developed a simulation and optimization framework combining different modeling schemes such as activity-based modeling, a location-allocation optimization tool, agent-based modeling, and health impacts modeling. For the activity-based modeling, the team developed simulation scenarios using the MTC-ABM model one, MATSIM for agents, and ITHIM for health.

The MTC-ABM scenarios focused on a series of parameter changes and travel assumptions to be able to simulate the ridesharing+transit service. The optimization algorithm used continuous approximation techniques to find the optimal PUDOs that minimized users' travel, access, and waiting times. The team developed a dedicated simulation in MATSIM, and modified ITHIM to account for the program characteristics and study area.

Overall, the team concentrated on purpose specific trips and simulation time periods. Specifically, work and shopping related trips. The time periods included AM and midday. The basic premises of the scenarios considered that the use of ridesharing to access transit would overcome age driving and car ownership limitations. Moreover, for users further away from transit stations, ridesharing could have different perceived access times and costs. The authors assumed perceived differences that ranged between 90% reductions up to a 100% increase for some of the cost and access time parameters.

In general, even for aggressive reductions in access time and costs, the resulting changes in system wide travel patterns are modest.

For example, assuming a 25% perceived reduction in drive time to BART resulted in an 8% increase in AM work trips using BART for a total of 72,404. From the 5,792 new BART trips, 1,077 trips switched from Drive-alone mode. For the 1,077 the results of the optimization showed an average walking time of 17 min., drive time of 20 min., and waiting time of 7 min. Around 60% of the travelers could have a combined walk and wait time between 5 to 20 mins, although there is a large portion of individuals that could experience more than 20 minutes, up to an hour of delay.

The MATSIM time and cost estimation revealed a large portion of trips with significant travel time increase that contributed to increases in general cost for 74% of trips as well. The trip cost (excluding the time cost) reduced for almost 68% of trips with a total value of around $5,000. From the vehicle perspective, total vehicle VMT decreased dramatically; however, 45% of the rideshare vehicle mileage is empty. Moreover, the optimistic 90% access time reduction for AM work trips only reduced overall VMT by 0.2% – 0.5% in peak hours.

In terms of health impacts, evaluating the combined shopping and work trip scenarios showed very small results, which are mostly determined by the small changes in travel activity. The program is not necessarily attractive for the largest segments of the population, and is not able to induce a mode shift from personal vehicles to transit. Consequently, there are not significant health impacts. However, when evaluating the direct impacts to the individuals shifting from drive alone to the ridesharing+transit service, the results show health and injury benefits between 2% and 11% (different reductions for the various evaluated diseases).

More importantly, the embedded behavioral models in MTC-ABM limited the study assessments. As a consequence, these models, their coefficients and elasticities affected the expected

behaviors to parameter changes. The empirical analyses showed that a percentual change in access time generated a larger change in behavior compared to the same change in cost.
There are other aspects that affect the ridesharing+transit program:

- Users locations (e.g., distance/access to BART);
- Origin-destination pairs (e.g., outside of BART service area);
- Trip purpose (e.g., work vs. shopping); and,
- Travelers' preferences and characteristics (e.g., income and other socio-demographic variables affecting travel choices).

Although the agent-based modeling results show mileage and cost reductions, increases in travel delay by almost all the trips seems to be a serious operational issue for encouraging demand to this mode. Improving the performance of transit lines and rideshare services through travel and wait time reductions can help mitigate the issues. Moreover, providing subsidies to those with high percentages of time lost may play an important role towards an effective long-term sustainable mobility. Better vehicle and demand allocation algorithms can also be an efficiency improvement with the aim of empty vehicle mileage reduction.
Overall, additional strategies are needed to foster transit and active transportation if the goal is to promote a sustainable environment. Ridesharing services, if they want to be a contributor to this goal, they have to avoid becoming a private vehicle alternative and seek to promote pooled ridership and complement other efficient modes.

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