Capital Region Mobility Hub Impact Assessment Report

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Executive Summary

Mobility hubs are places of transit connectivity where different travel options like walking, biking, bus service, and shared mobility come together. The motivation of building a mobility hub is to improve the accessibility, effectiveness, and efficiency of public transit by enabling multimodal trips, as well as to reduce private car usage, vehicle mile traveled, and carbon dioxide emissions. However, the main challenge in accessing the potential impacts of mobility hubs is that there is no consistent population travel data or ground truth data reflecting the actual usage of mobility hubs. On one hand, large scale travel data remains scarce, particularly for underserved and rural communities. On the other hand, most of the mobility hubs are at the conceptual stage and few have been implemented.

This is changing with the practice of real-case mobility hubs and the availability of large-scale information and communication technology (ICT) data. Capital District Transportation Authority (CDTA) initiated the Capital Region Mobility Hubs Demonstration Project from April 2022 to June 2024, to test out two mobility hubs, one in UAlbany Downtown Campus and one in Downtown Cohoes and to determine the feasibility of scaling these mobility hubs across the state. As of the writing of this report, December 2023, these two mobility hubs have already been implemented for several months, providing ground truth data of real-case mobility hub usage and the opportunity to conduct on-site surveys. Moreover, Replica Inc. developed a nationwide synthetic population dataset that includes both sociodemographic information and trip/activity details. According to their data quality report, sociodemographic attributes of the synthetic population are 95% accurate compared with census data, and the trip mode share by census tract is 90% accurate compared with Census Transportation Planning Products (CTPP) data. Behavioral models for a wide range of different population segments can be developed using this unique data opportunity. With the combination of real-case mobility hub usage and large-scale pre-trained model, it is now possible to overcome the challenge of limited sample size and assess the broader impacts of mobility hubs, i.e., to capture hub user preference, to forecast ridership and vehicle miles traveled (VMT), and to measure change in consumer surplus (compensating variation) in the post-pilot scenario.

This report focuses on the impact assessment of this project's two mobility hubs. To collect ground truth usage data, we designed an on-site survey and received 40 useful responses from October to December 2023. CDTA also provided their backend data for DRIVE usage (a car share service available in the mobility hub) and transit ridership to/from those hub stations. For the pre-trained behavioral model, we used a set of New York State mode choice models (one per origin-destination pair at Census block group level) developed with Replica's data in a previous project. The model contains agent-specific coefficients that can be used to quantify the mode choice for every census block group to block group pair, segmented by age, income level, and employment status. This model is publicly available at https://zenodo.org/record/8113817. To combine the ground truth data and the mode choice model, we proposed an approach to estimate unique mobility hub preferences to fit to the ground truth usage. The impact was then measured by comparing the post-pilot deployment demand and usage of the two mobility hubs against a baseline prior to deployment, from the perspective of predicted mode shift, reduced VMT and carbon dioxide emissions, and increased expected consumer surplus (i.e., quantified willingness of travelers to pay for such benefits).

We found that the mobility hubs introduced more multimodal trips (those that transfer from one mode to another), and we showed which current direct modes these trips drew from. In short, the hub in UAlbany Downtown Campus introduced 8.83 trips per day, resulting in a decrease of 20.37 thousand vehicle miles traveled (VMT) per year and a decrease of 8.15 metric tons of carbon emissions per year. The hub in Downtown Cohoes introduced 6.17 trips per day, resulting in a decrease of 13.16 thousand VMT per year and a decrease of 5.27 metric tons of carbon emissions per year. The decrease of carbon emissions is roughly equivalent to two household's carbon footprints in a year. The implementation of mobility hubs brought an increase of utility to their potential trips, which was further transformed into monetary value by dividing the coefficients of trip monetary cost. We showed that the UAlbany hub brought an increase monetary value of \$0.195/trip, and the Cohoes hub brought an increased monetary value of \$0.319/trip. In a hypothetical scenario in which the bus service is free for trips using the mobility hub, we showed that there would be a further increase of bus trips (+4.93 trips/day), a further reduction in VMT (9.7 thousand vehicle-miles-traveled/year), a further reduction in carbon emission (-3.99 metric tons/year), a further increase in trip monetary value (+\$0.06/trip), while at the cost of losing total revenue collected at the hubs (-\$30.75/year).

The key to the success of mobility hubs is finding the best site location, hub density, and pricing policy to encourage more travelers to use them in a broader range. For further studies, the calibrated model in this report is scalable to evaluate the impacts of different pricing policies and pick candidate locations to deploy new mobility hubs. Additional data collected would further improve the accuracy of these models. Could be more specific.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Definition
CDTA	Capital District Transportation Authority
CTPP	Census Transportation Planning Products
DCM	Discrete choice model
ICT	Information and communication technology
OD	Origin and Destination
VMT	Vehicle miles traveled

1. Introduction

1.1. Background

Mobility hubs are places of transit connectivity that allow for efficient integration of multiple public modes (like walking, biking, bus service, and shared mobility options), enabling more comfortable, cost and time efficient travel than those achieved by single trip modes (Miramontes et al., 2017). The motivation of building a mobility hub is to improve the accessibility, effectiveness, and efficiency of public transit by enabling multimodal trips, as well as to reduce private car usage, vehicle mile traveled, and carbon dioxide emissions (Aydin, Seker and Özkan, 2022; Ku et al., 2022). As shown in **Figure 1.1**, mobility hubs are strategically designed locations that integrate private vehicle, linear public transport, and other transportation modes. Typically situated at key transit points, mobility hubs serve as focal points for multimodal trip options, by providing real-time information displays, secure bike storage, or user-friendly interface to facilitate easy transfers between modes. The concept of mobility hubs aligns with the goal of creating more sustainable and accessible mobility services while addressing the increasing travel demands of diverse communities (Czarnetzki and Siek, 2023).

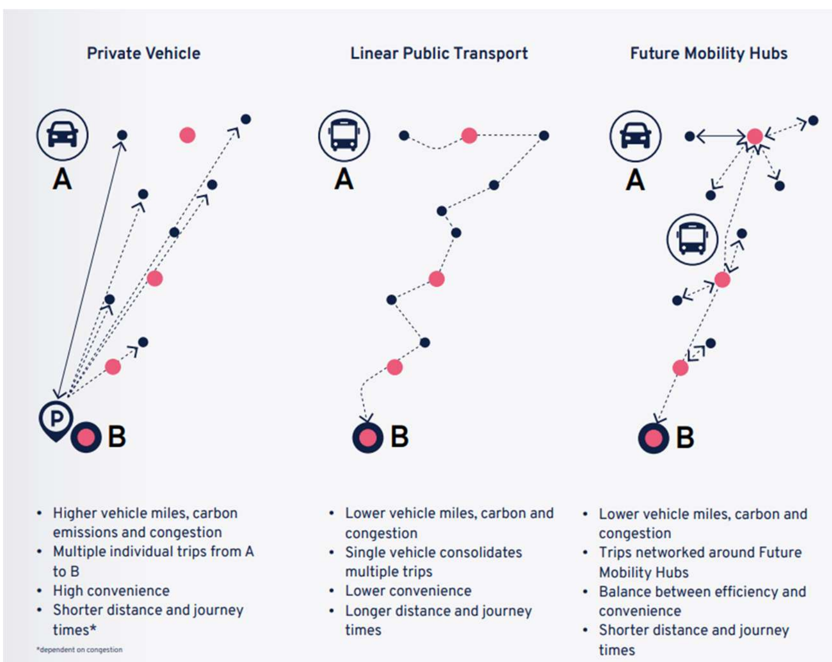
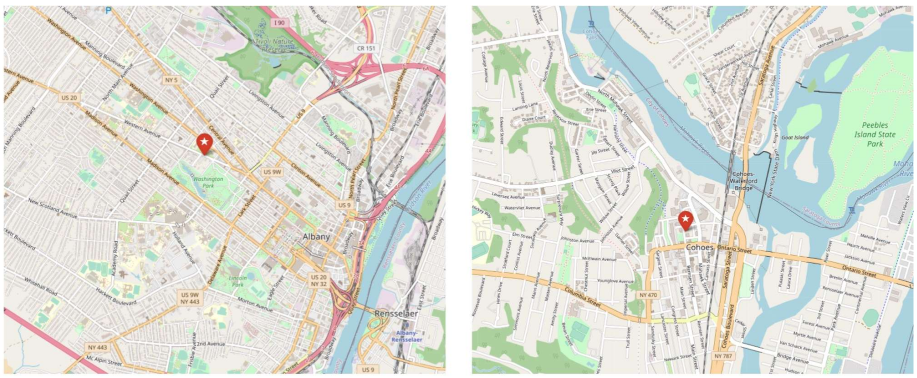


Figure 1.1. The concept of mobility hubs (source: Arup, Future Mobility Hubs)

However, assessing the success or potential impacts of a mobility hub is challenging mainly due to two reasons. First, most of the mobility hubs are at their conceptual stage and few of them have been implemented. The lack of real-case usage data makes it harder to get user feedback and capture user preference of the mobility hubs. Second, a mobility hub entails a wide range of mode combinations as well as trip origin and destination pairs, while large scale travel data remains scarce, particularly for underserved and rural communities.



UAlbany Downtown Campus Downtown Cohoes

Figure 1.2. Locations of the two mobility hubs

This is changing with the practice of real-case mobility hubs and the availability of information and communication technology (ICT) data. Capital District Transportation Authority (CDTA) initiated the Capital Region Mobility Demonstration Project from April 2022 to June 2024 to test out two mobility hubs, one in UAlbany Downtown Campus and one in Downtown Cohoes (see **Figure 1.2**), and to determine the feasibility of scaling their mobility hubs across the state. As of December 2023, these two mobility hubs have already been implemented for several months, providing an opportunity to collect onsite survey data reflecting the actual usage of mobility hubs. Moreover, Replica Inc. developed a nationwide synthetic population dataset that includes both sociodemographic information and trip/activity details. Behavioral models for a wide range of different population segments can be developed using this unique data opportunity (Ren and Chow, 2023). With the combination of real-case mobility hub usage and large-scale pre-trained models, it is now possible to overcome the challenge of a limited sample size and assess the broader impacts of mobility hubs, i.e., to capture hub user preference (Zuurbier, 2023), to forecast transit ridership (Wu and Liao, 2020), to calculate vehicle miles traveled (VMT) (Shin, 2020), and to measure change in consumer surplus in the post-pilot scenario (McHardy, Reynolds and Trotter, 2023).

1.2. Objectives

This report focuses on the impact assessment of the UAlbany Downtown Campus and Downtown Cohoes mobility hubs. Ground truth mobility hub usage data were integrated into a mode choice model estimated with Replica's synthetic population data. The impact was then measured by comparing the post-pilot deployment demand and usage of the two mobility hubs against a baseline prior to deployment, from the perspective of predicted mode shift, reduced VMT and carbon dioxide emission, and increased consumer surplus. Three objectives were identified.

Objective 1: Mobility Hub Survey Design and On-site Response Collection

The first objective was to design a mobility hub survey and collect on-site responses. Since the mobility hubs in UAlbany Downtown Campus and Downtown Cohoes have already been implemented, we had the opportunity to collect trip details using the mobility hub, including trip purpose, trip frequency, trip origin and destination (zip code level), trip mode before and after using the mobility hub, trip monetary cost, alternative transport modes without the mobility hub, and motivations of using the mobility hub. We also collected user information such as gender, age, employment status, household size, income level, car ownership, and CYCLE! membership. This data gave us a direct view of how travelers use the mobility hub.

Objective 2: Calibrating Mobility Hub-related Coefficients upon the Pre-trained Model

Till now we have collected 40 responses of the survey. These responses could serve as ground truth mobility hub usage data to be integrated into a large-scale pre-trained mode choice model, predicting mode shift brought by the mobility hub with a wide range of trip origin-destination (OD) pairs and population segments. Therefore, the second objective was to use the ground truth data to *re-calibrate mobility hub-related coefficients* in the pre-trained model. We used a set of New York State mode choice models developed with Replica's 2019 data in a previous project. The model contains agent-specific coefficients that could be used to quantify the mode choice for every census block group to block group pair, segmented by age, income level, and employment status. To combine the ground truth data and the mode choice model, we proposed an approach to estimate unique mobility hub preferences to fit the ground truth usage.

Objective 3: Impact Assessment with the Calibrated Model

Once the mobility hub-related coefficients were calibrated, the model could then be used to predict travelers' mode choice given the multimodal trip options with the mobility hubs. The mobility hub demonstration impact was then measured by comparing the post-pilot deployment demand and usage of the two mobility hubs against a baseline prior to deployment, from the perspective of:

- **Increased transit activity:** this was measured by observing samples of mode choices in post-deployment among users of the mobility hubs, extrapolating that to population level, and comparing that to the pre-deployment baseline.
- **Reduced vehicle miles traveled (VMT):** based on the modes chosen by the population, we approximated the VMT for all the modes combined.
- **Environmental impacts:** regarding the VMT, we used EPA values[1] for carbon emissions to assess environmental impacts.
- **Increased consumer surplus:** consumer surplus is widely used in economic welfare measurement with discrete choice models (McConnell, 1995). We used it as one of the impact indicators and transform its unit into dollars per trip using the coefficient of trip cost.

[1] https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle

2. Overview of Literature

2.1. Concept and Benefits of Mobility Hubs

Mobility hubs are highly visible, safe, and accessible spaces where public, shared, and active travel modes are coordinated, alongside improvements to the public realm and relevant enhanced community facilities (Arnold et al., 2023). According to existing studies, three major advantages can be derived—the vitalization of public transportation, environmental benefits, and multimodal trip options. These three advantages are discussed below. The mobility hub is an effective way to promote the use of public transportation. Optimal integration between different types of public transit has a significant impact on the flow of cities and allows people to use public modes more often (Stiglic et al., 2018). Bus lines, railways, and inter-connected stations allow travelers to go anywhere they want (Huang et al., 2018). Therefore, when transfers become less inconvenient, the use of public transportation becomes more active (Bueno, 2021). The creation of a good transfer environment involves creating a transport hub with the optimization of public transport services (Miramontes et al., 2017).

It is possible to reduce greenhouse carbon dioxide emissions by reducing vehicle travel distance through the implementation of mobility hubs (Claasen, 2020). Sharing mobility is helpful in reducing carbon emissions. If every travel mode in the mobility hub is optimized by convenient and efficient transferring ways, called a boosting metabolism, it brings more environmental benefits (Marsden et al., 2019).

Mobility hubs provide multimodal trips that are not restricted to public transportation. For instance, one can drive their private car to the mobility hub, park the vehicle there, and take a bus to the final destination in which driving is inconvenient due to road congestion and lack of parking lots. Also, one can take a bus to the mobility hub and rent a shared bike for the last mile trip. The combination of driving, carpooling, biking, and public transit makes trips with the mobility hub more efficient, in terms of travel time or monetary cost (McHardy, Reynolds and Trotter, 2023).

To this end, the impact of mobility hub demonstration should be assessed from these three aspects, including:

1) the increase of public transit ridership,

2) the reduction of private vehicle miles traveled (VMT) and carbon emission, and
3) the increase of trip experience.

Measurements of all these impacts depend on the prediction of travelers' choice given different trip mode options with the mobility hub.

2.2. Choice-based Impact Assessment Techniques

2.2.1. Discrete Choice Models (DCMs) for Behavioral Choice

DCMs are economic models used to analyze and predict the choices individuals make when presented with a set of distinct alternatives. DCMs assume individuals make choices by maximizing the overall utility they can expect to gain (Bowman and Ben-Akiva, 2001), and they have been widely used to predict travelers' mode choices. Advanced DCMs for behavioral choice can be divided into two categories. The first category treats choice dimensions with a nested structure, in the sequence from time frames to travel modes and from mode choice to route choice (Horni et al., 2016; Bowman and Ben-Akiva, 2001). A basic form is the nested logit model (NL) while a more advanced one follows a Markov decision process (MDP) and models choices as dynamic DCMs (Aguirregabiria and Mira, 2010; Västberg et al., 2020). Dynamic DCMs assume that individual $i \in P$ acts to maximize the utility function defined by Eq. (2.1).

$$U_{ijt} = x_{ijt}b_{jt} + e_{ijt} + m_t EV(i,j,t)\,, \qquad \forall i \in P, \forall j \in J, \forall t \in T \tag{2.1}$$

where t denotes the choice situation or time period. x_{ijt} denotes a set of observed variables of individual i choosing alternative j in situation t. b_{jt} is a set of coefficients reflecting preferences. $x_{ijt}b_{jt}$ and e_{ijt} denotes the deterministic and random utility, which is aligned with conventional DCMs. $EV(i,j,t)$ is the expected utility of all possible alternatives in the remainder of the day, usually calculated using multi-dimensional integrals or backward induction with a relatively high computational cost (Västberg et al., 2020). m_t is a coefficient defining the weight of expected utility in choice situation t. Accordingly, the probability of individual i choosing alternative j in situation t is defined as Eq. (2.2).

$$P_{ijt} = \frac{e^{x_{ijt}b_{jt}+e_{ijt}+mEV(i,j,t)}}{\sum_{j'\hat{I}J} e^{x_{ij't}b_{jt}+e_{ij't}+mEV(i,j',t)}}, \quad \forall i \in P, \forall j \in J, \forall t \in T \tag{2.2}$$

The second category focuses on stochastic heterogeneity models, considering that preference may vary across different choice situations of different individuals. Up to this point, logit mixtures incorporating inter- and intra-individual heterogeneity are estimated with a maximum likelihood procedure (Becker et al., 2018; Krueger et al., 2021). For example, a mixed logit model (MXL) assumes that each individual i faces a choice among J alternatives. Then, the utility associated with each alternative $j = 1, \ldots, J$ for individual i is defined as Eq. (2.3).

$$U_{ij} = x_{ij}b + e_{ij}, \qquad \forall i \in P, \qquad \forall j \in J \tag{2.3}$$

where x_{ij} denotes a set of observed variables of individual i choosing alternative j. e_{ij} is the random utility. The vector of tastes b is assumed to be a variate that varies across individuals according to $g(\mathrm{b}|\mathrm{W})$, where $g(.)$ is usually the Gaussian distribution with the mean and covariance included in W. Accordingly, the probability of individual i choosing alternative j is defined as Eq. (2.4).

$$P_{ij} = \int \frac{e^{x_{ij}b}}{\sum_{j'\hat{I}J} e^{x_{ij'}b}} g(b|\mathrm{W})db, \quad \forall i \in P, \qquad \forall j \in J \tag{2.4}$$

Despite a growing number of empirical studies, DCMs are not designed for equity analysis under the Big Data context (Ren and Chow, 2022). With a ubiquitous dataset, attributes from the whole population can be obtained instead of just from a sample (Ahas et al., 2009), and the individual tastes might not be normally distributed due to lacking personal information (Zhao, Pawlak and Polak, 2018). To this end, modelers should consider individual-specific estimations without complex assumptions of the conditional distribution.

2.2.2. Machine Learning Methods for Behavioral Choice

In recent years, there has been an emerging trend of using general-purpose machine learning models (MLs) to analyze individual choices (Wang et al., 2020b). General-purpose MLs for behavior choice have both pros and cons. The pros are that these models allow flexible relationships between individuals' choices and explanatory variables, resulting in higher prediction accuracy than classical DCMs (Hagenauer and Helbich, 2017; Omrani, 2015; Pulugurta et al., 2013). The cons are that MLs are often criticized as "black-boxes" that are sensitive to hyperparameters and lack interpretability for modelers to explain the behavioral mechanism (Liao and Poggio, 2018; Sun et al., 2019; Wang et al., 2020b).

Besides the pros and cons widely discussed in existing studies, general-purpose machine learning models do not generally address the limitations of DCMs. On the one hand, similar to the likelihood functions in DCMs, cross-entropy-based cost functions in MLs are also inefficient to optimize, given a huge dataset. On the other hand, though the powerful automatic learning of MLs can capture complex behavior realism, it is at the cost of local irregularity and non-linearity of demand functions (LeCun et al., 2015; Liao and Poggio, 2018). Wang et al. (2020a) have pointed out the impacts of local irregularity on individual tastes. They found that the exploding and vanishing gradients in neural networks can result in extremely high or low sensitivities at the individual level that are opposite to domain knowledge. Moreover, with hundreds of parameters in deep learning models, it is almost infeasible to formulate the utility function, let alone generate demand functions and integrate them into optimization models. An innovative, domain-specific machine learning approach is necessary to deal with the ubiquitous datasets and build the link between demand and supply.

2.2.3. Inverse Optimization (IO) for Behavioral Choice

Inverse optimization (IO) is initially used to impute missing optimization model coefficients from data that represents sub-optimal solutions of that optimization problem (Ahuja and Orlin, 2001; Burton and Toint, 1992). Given an optimization problem, an IO can be formulated to impute its left-hand-side constraint parameters and feasible regions (Ghobadi and Mahmoudzadeh, 2021). A typical IO problem is defined as follows: for a given prior q_0 of missing coefficients and observed decision variables x^*, determine an updated coefficient set q such that x^* is optimal while minimizing its L_1 norm from the prior, as shown in Eq. (2.5).

$$\min_q |q_0 - q\,| : x^* = \arg\min \{q^T x : Ax \leq b, x \geq 0\} \tag{2.5}$$

where A is the constraint matrix b is the vector of side constraint values. $Ax \leq b$ are constraints ensuring x^* is optimal (or the best choice). L_1 norm from a prior is used to regularize what would otherwise be an ill-posed problem with infinite solutions. Ahuja and Orlin (2001) proved that Eq. (3.5) can be reformulated as a linear programming (LP) problem.

Though IO is less popular than general-purpose machine learning models, it has already been applied to traffic assignment, route choice, and activity scheduling problems (Chow and Recker, 2012; Hong et al., 2017; Chow, 2018; Xu et al., 2018). For instance, Chow and Recker (2012) proposed a multiagent framework for IO where a sample of individuals' trip scheduling data is obtained and used to infer parameters of individual activity scheduling. Xu et al. (2018) formulated the multiagent inverse transportation problem to estimate heterogeneous route preferences and proved that the IO approach could obtain heterogeneous link cost coefficients even when multinomial or mixed logit models would not be meaningfully estimated. Moreover, the potential of IO in modeling individual choice has been noticed by existing studies. Iraj and Terekhov (2021) emphasized the need for stochastic IO models in scenarios where constraints, objective, and prior parameters can be defined with domain knowledge.

2.2.4. Consumer Surplus with Calibrated User Preference

Consumer surplus (also called 'measure of accessibility') is an economic measurement of consumer benefits resulting from market competition, which measures the scalar summary of expected 'worth' of the set of services or products (Small and Rosen 1981). In the context of discrete choice model (DCM) with the assumption of utility maximization, the expected consumer surplus for individual n given the choice set C_n is defined in Eq. (2.6).

$$E\left[\max_j U_{jn}\right] = \frac{1}{\alpha_n} \ln \sum_{j \in C_n} e^{mV_{jn}} + c \tag{2.6}$$

where V_{jn} is the utility of individual n choosing alternative j based on user preference estimated by models introduced in Section 2.2.1-2.2.3; m is a scale factor for the utility that is usually assumed equals to 1; α_n is the marginal utility of income that is usually correlated with individual $n's$ taste coefficient of monetary cost; c is an unknown constant. Due to the unknown constant, evaluating consumer surplus on its own Is pointless, but since c is unique to individual, it is possible evaluate the change of it among scenarios. Small and Rosen (1981) proposed the measure of compensating variation (CV) – the amount an individual should be compensated to be as well off as before a policy change, which is defined in Eq. (2.7).

$$\Delta CV = \frac{1}{\alpha_n}\left[\ln \sum_{j \in C_n^2} e^{\mu V_{jn}^2} - \ln \sum_{j \in C_n^1} e^{\mu V_{jn}^1}\right] \tag{2.7}$$

where V_{in}^1, V_{in}^2 are utilities before and after the implementation of a policy, C_n^1, C_n^2 are choice sets before and after the implementation of a policy. In this report, the policy refers to the deployment of two mobility hubs, C_n^1 only contains single-modal trip options while C_n^2 also contains multimodal trip options using the mobility hub. Since we do not have enough information for individuals' marginal utility of income, we use a common assumption, i.e., α_n equals to the coefficient of individual n's coefficients of monetary cost. In that case, the unit of CV (or change of consumer surplus) should be 'dollars/trip'.

2.3. Research Gap

Ground truth mobility hub usage data and large-scale mode choice model are complementary to each other. On-site survey data are limited in sample size considering the labor cost (maybe not feasible to build a simple DCM), which requires the support of a large-scale pre-trained model to make it representative for a wide range of trip OD pairs and population segment. In addition, most large-scale mode choice models are not designed to consider mobility hub trips (since the implementation of mobility hubs is one its early stage), which require real-case user preference data to calibrate part of the coefficients.

However, there is a lack of an approach to integrate ground truth data into pre-trained mode choice models. Such an approach is similar to the zero/one shot learning for pre-trained deep learning models (Xian et al., 2018), and should be the key to assessing the broader impacts of mobility hubs. With such an approach, we captured hub user preference to forecast ridership and vehicle miles traveled (VMT), and then measured the change in consumer surplus (compensating variation) in the post-pilot scenario.

3. Proposed Methodology

The scope of our methodology is shown in **Figure 3.1**, which contains three parts: (1) ground truth data collection; (2) integrating ground truth data into the pre-trained mode choice model; (3) impact assessment with the calibrated model. The following subsections introduce them one by one.

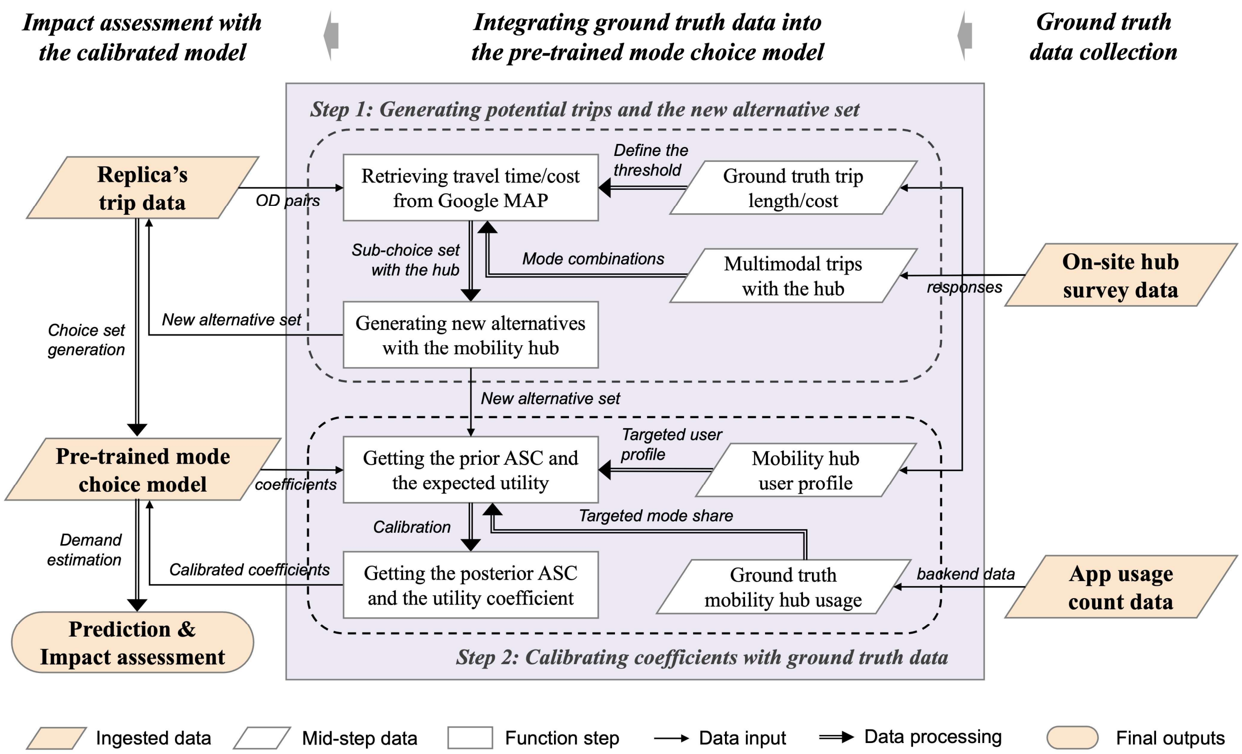


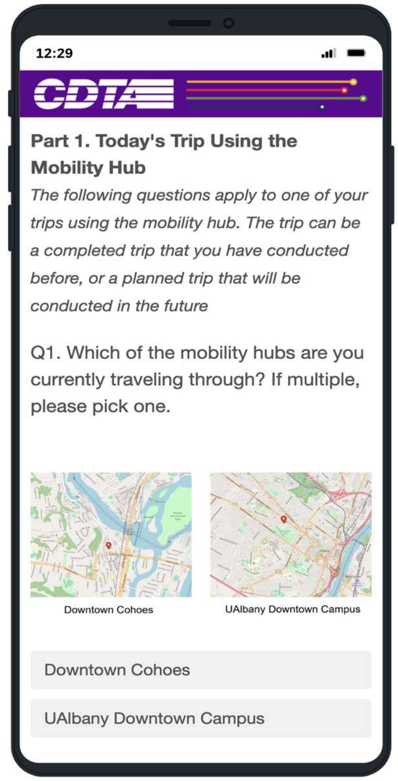
Figure 3.1. Flow chart of mobility hub impact assessment

3.1. Ground Truth Data Collection

3.1.1. Questionnaire Design

To get the real-case mobility hub usage, a questionnaire was developed to target current and potential users of the mobility hubs in Downtown Cohoes and UAlbany Downtown Campus. The content of the questionnaire consisted of two parts:

- Today's trip using (or potentially using) the mobility hub, including trip purpose, trip frequency, trip origin and destination (zip code level), trip mode before/after using the mobility hub, trip monetary cost, alternative transport modes without the mobility hub, and motivations of using the mobility hub.
- Personal information that helps us to identify population segments, including gender, age, employment status, household size, income level, car ownership, and CYCLE! membership.



The first part contains 8 questions concerning details of a real (potential) trip using the mobility hub. These trip details are related to people's intention to use certain means of transport available at the hub. For trip origin and destination, we asked respondents to fill the full address or fill the zip code from which we could get a rough location for analysis. For trip monetary cost, we asked respondents to fill in dollars. The rest of the questions were asked using multiple answer options.

The second part of the survey contains 7 questions concerning personal information. This information is used to identify population segments (or user portraits) that might influence people's sensitivity to travel time and cost, as well as preference to specific transport mode at the hub. All questions were asked using multiple answer options with an additional option of "prefer not to say". For a more detailed overview of the questionnaire, please see the publicly available version accessible at https://nyu.qualtrics.com/jfe/form/SV_9sHTmTbDu18ORng.

We received 40 useful responses for analysis. Most of these responses were received from October through December (**Figure 3.2a**). Among the 40 responses, 22 of them were collected in UAlbany Downtown Campus and 18 of them were collected in Downtown Cohoes (**Figure 3.2 b**). Using these responses, we could get the rough user profile and trip details using the mobility hub.

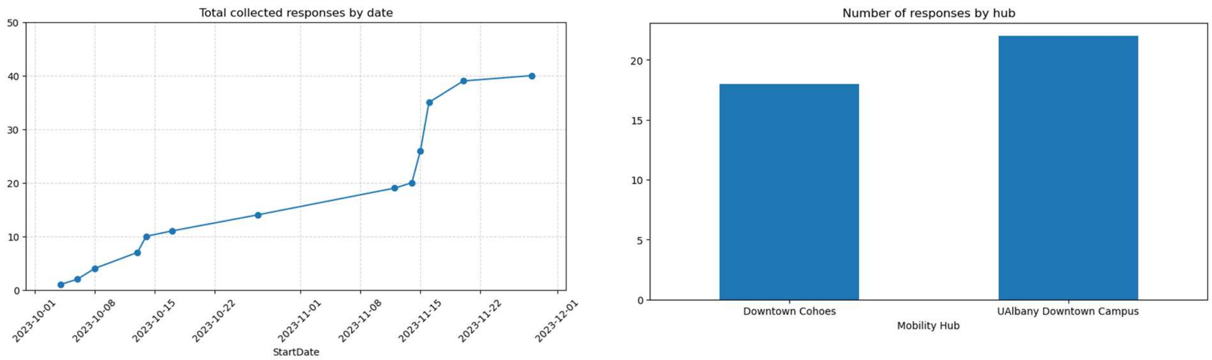


Figure 3.2. Number of responses by date and mobility hub

Demographics of the respondents:

- **Gender:** 52.4% of respondents were female, 42.9% of respondents were male, 4.7% of respondents preferred not to say.
- **Age:** 11.9% of respondents were between 19-20, 11.9% of respondents were between 21-24, 14.3% were between 25-34, 9.5% were between 35-44, 11.9% were between 45-54, 16.7% were between 55-64, 14.3% were between 65-74, 2.4% were over 75, 7.1% preferred not to say
- **Employment status:** 42.9% of respondents were working full or part time, 16.7% of respondents were full or part time student, 21.4% of respondents were retired, 9.5% were not working, and 7.1% of respondents were both working and park-time students, 2.4% preferred not to say.
- **Household size:** 40.5% of respondents were from single-member household, 26.2% of respondents were from two-member household, 9.5% were from three-member household, 14.3% were from four-member household, 9.5% were from household with more than four members.
- **Household annual income:** 9.5% of the respondents were less than \$10K, 9.5% of the respondents were between \$10K-\$15K, 14.3% were between \$15K-\$25K, 4.8% were between \$25K-\$35K, 11.9% were between \$35K-\$50K, 9.5% were between \$50K-\$75K, 4.8% were between \$75K-\$100K, 11.9% were more than \$100K, 23.8% of respondents preferred not to say.
- **Car ownership:** 47.6% of respondents did not have any private vehicle, 33.3% of respondents owned one private vehicle, 19.0% of respondents owned more than one private vehicles.
- **Bicycle or CYCLE! membership:** 63.4% of respondents did not have bicycle or CYCLE! membership, 22.0% of respondents had a bicycle without CYCLE! membership, 7.3% of

respondents had a CYCLE! membership without a bicycle, 7.3% of respondents both had a bicycle and a CYCLE! membership.

Trip details using (or potentially using the hub):

- **Motivations of using the hub:**
    - To decrease my overall trave time (18 responses);
    - To decrease my overall travel cost (16 responses)
    - I wanted to incorporate exercise to my travel plans (7 response)
    - It is a more enjoyable trip (3 response)
    - My ability to plan and pay for the entire trip in one app (5 response)
    - It was an environmental choice (8 responses)
    - Other reasons (7 responses)
- **Trip purpose:** 18.2% of respondents were for commuting to or from work, 25% of respondents were for commuting to or from school, 6.8% of respondents were for leisure and exercise, 34.1% of respondents were for shopping or errands, 15.9% were for other purpose (**Figure 3.3**).

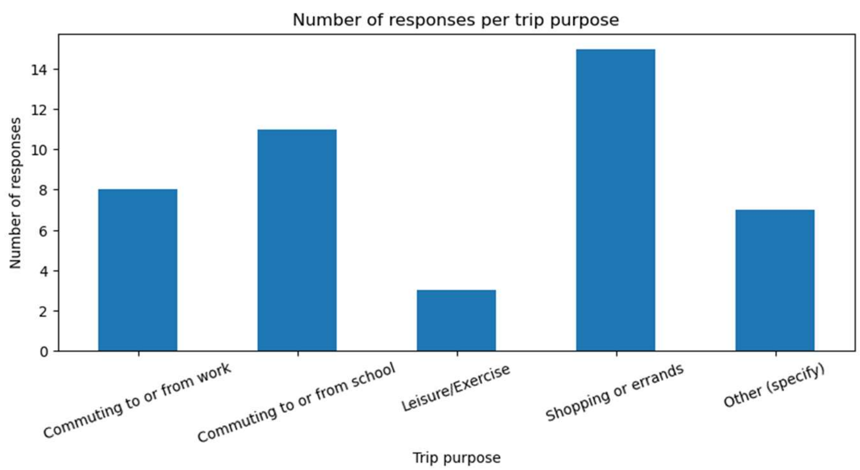


Figure 3.3. Number of responses by trip purpose

- **Trip frequency:** 9.1% of respondents conducted such a trip for the first time, 4.5% of respondents conducted such a trip 1-5 days a year, 6.8% of respondents conducted such a trip 6-11 days a year, 13.6% respondents conducted such a trip 1-3 days a month, 36.4% of respondents conducted such a trip 1-3 days a week, 29.5% of respondents conducted such a trip 4 or more days a week (**Figure 3.4**).

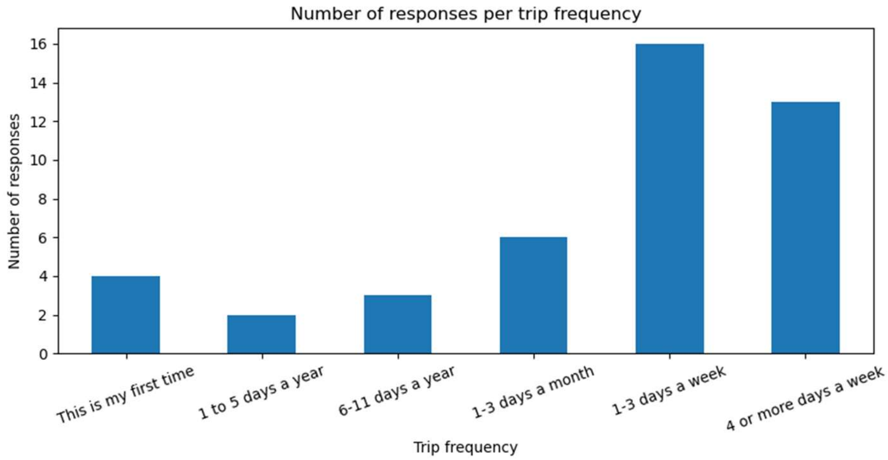


Figure 3.4. Number of responses by trip frequency

- **Trip origin & destination (poor data quality):** some of the respondents provided full addresses while others provided a place name or zip codes.
- **Primary trip mode:** most of the respondents took bus before/after entering the hub, and we did not find a respondent using scooter or bike (might be due to sample bias) (**Figure 3.5**).

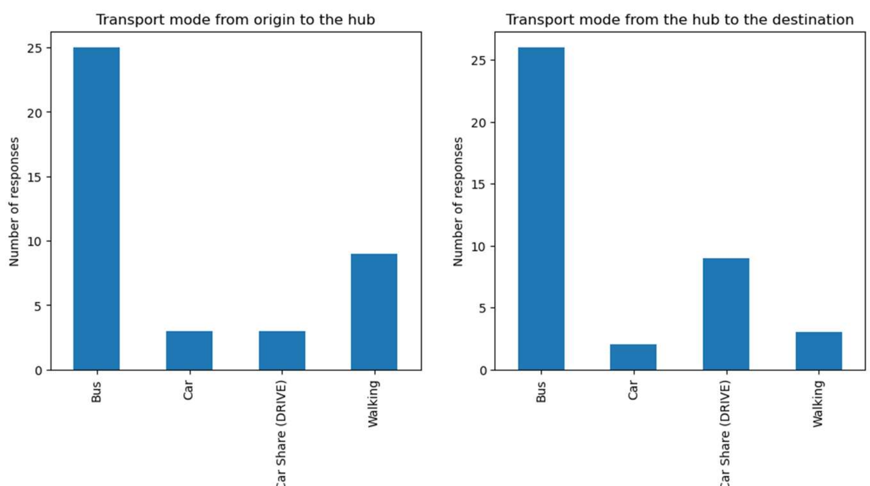


Figure 3.5. Number of responses by mode of the first and second trip segment

- **Trip monetary cost (poor data quality):** trip monetary cost was between $0-5 with some blank values.

3.1.2. App Backend Data

Besides the on-site survey data, CDTA also provided backend data from DRIVE (an app providing carpool service with a $5/hour fee). DRIVE data includes total revenue, monthly number of trips, rental time, and number of active members for each month. **Figure 3.6** shows the monthly trip data provided by CDTA, which was used to estimate a general proportion of trips using the mobility hub and calibrate our hub-related coefficients. **Note that DRIVE is not available at the UAlbany Downtown campus hub, so we only used the data for the Downtown Cohoes hub.**

Month	City of Cohoes
January 2023	5
February 2023	15
March 2023	26
April 2023	22
May 2023	27
June 2023	21
July 2023	16
August 2023	34
September 2023	25
October 2023	28
November 2023	22
Total	**241**

Figure 3.6. Monthly number of trips using DRIVE by each month

Moreover, CDTA also provided backend trip counts for bus and Cycle! (a bike share service). According to the bus trip counts, there were 267 pick-up trips per weekday and 192 drop-off trips per weekend at Downtown UAlbany Campus in October, and there were 234 pick-up trips per weekday and 220 drop-off trips per weekend at Downtown Cohoes Station in October. According to the Cycle! data, from September to mid-November there were 185 trips started and 130 ended at the UAlbany Downtown Campus hub (2.47 and 1.73 trips per day), and there were 37 trips started and 33 trips ended at the Downtown Cohoes hub (0.49 and 0.44 trips per day). These datasets were used to validate our calibration results.

3.2. Integrating Ground Truth Data into the Pre-trained Mode Choice Model

The key part of our methodology was the approach to integrate ground truth data into the pre-trained mode choice model. We proposed such an approach because our survey data had limited sample size and missing values in some fields, which might not be feasible to estimate a simple discrete choice model. Another reason is that we wanted to assess the impacts of mobility hubs on a broader range of trip OD pairs, which is only possible by retrieving coefficients from a pre-trained model. We used a New York State mode choice model developed with Replica's data in our previous project (publicly available at https://zenodo.org/record/8113817). The model contains agent-specific coefficients that can be used to quantify the mode choice for every census block group to block group pair, segmented by age, income level, and employment status.

3.2.1. Initial Settings

In the pre-trained model, six initial trip modes were considered, including private auto, transit, on-demand auto, biking, walking, and carpool. Four mutually exclusive population segments are separated, namely not-low-income population, low-income population, senior population, and student population. First, student population included all individuals that are full-time students. Then senior population included individuals whose age is no less than 65. Finally, the identification of not-low-income and low-income population was based on U.S. Federal Poverty Guidelines[2], in which a low-income household was defined as household annual income bellowing a threshold given a particular household size.

For a given agent i (by trip OD pair and population segment), the utility of choosing the six initial modes is defined in Eqs. (3.1) – (3.6).

$$V_{private\_auto,i} = \theta_{auto\_tt,i} time_i^{private\_auto} + \theta_{cost,i} cost_i^{private\_auto} + asc_{auto,i}, \quad \forall i \in I \tag{3.1}$$

$$\begin{aligned} V_{public\_transit,i} = {} & \theta_{transit\_at,i} access\_t_i + \theta_{transit\_et,i} egress\_t_i + \theta_{transit\_ivt,i} in\_vehicle\_t_i \\ & + \theta_{transit\_trans,i} num\_transfer_i + \theta_{cost,i} cost_i + asc_{transit,i}, \quad \forall i \in I \end{aligned} \tag{3.2}$$

$$V_{on\_demand,i} = \theta_{auto\_tt,i} time_i^{on\_demand} + \theta_{cost,i} cost_i^{on\_demand} + asc_{on-dem,i}, \quad \forall i \in I \tag{3.3}$$

$$V_{biking,i} = \theta_{non\_auto\_tt,i} time_i^{biking} + \theta_{cost,i} cost_i^{biking} + asc_{biking,i}, \quad \forall i \in I \tag{3.4}$$

$$V_{walking,i} = \theta_{non\_auto\_tt,i} time_i^{walking} + \theta_{cost,i} cost_i^{walking} + asc_{walking,i}, \quad \forall i \in I \tag{3.5}$$

[2] https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines/prior-hhs-poverty-guidelines-federal-register-references/2019-poverty-guidelines

$$V_{carpool,i} = \theta_{auto\_tt,i} time_i^{carpool} + \theta_{cost,i} cost_i^{carpool}, \qquad \forall i \in I \tag{3.6}$$

where i denotes the unique ID of an agent (composed of origin block group id, destination block group id, and population segment id); I is the set of total agents; $V_{private\_auto,i}$, $V_{public\_transit,i}$, $V_{on\_demand,i}$, $V_{biking,i}$, $V_{walking,i}$, $V_{carpool,i}$ are utilities of trips using six initial modes; $time_i^*$ and $cost_i^*$ are the travel time and monetary cost of different modes; $access\_t_i$, $egress\_t_i$, $in\_vehicle\_t_i$, $\theta_{transit\_nt,i}$ are the access time, egress time, in-vehicle time, and number of transfers for public transit. All these observed variables are from Replica's synthetic data, and $\theta_{auto\_tt,i}$, $\theta_{transit\_at,i}$, $\theta_{transit\_et,i}$, $\theta_{transit\_ivt,i}$, $\theta_{transit\_nt,i}$, $\theta_{transit\_trans,i}$, $\theta_{cost,i}$, $asc_{auto,i}$, $asc_{transit,i}$, $asc_{on-dem,i}$, $asc_{biking,i}$, $asc_{walking,i}$ are 12 coefficients per OD pair of our pre-trained model.

Now with the demonstration of the mobility hub, there would be a new alternative set with all multimodal trip options using the hub (C_{hub}), and the utility of choosing a specific mode transfer at the mobility hub $V_{m1-m2,i}^{hub}$ is defined in Eq. (3.7). Given travel time and cost, all of the items in Eq. (3.7) can be calculated using our pre-trained model.

$$V_{m1-m2,i}^{hub} = V_{m1,i} + V_{m2,i}, \qquad \forall i \in I \tag{3.7}$$

where $m1$ is the trip mode from the origin to the hub; $m2$ is the trip mode from the hub to the destination; $m1$ and $m2$ belongs to the choice set consisting of six initial modes. Given an available mode transfer with the hub, say 'Car—Hub—Bus', the probability of travelers in agent i choosing this multimodal trip option equals to the probability of choosing the alternative set using the hub times the probability of choosing the specific mode combination in the alternative set, as shown in Eq. (3.8) – (3.11).

$$P_i(car - bus|J) = P_i(hub|J) * P_i(car - bus|J_{hub}), \qquad \forall i \in I \tag{3.8}$$

$$P_i(car - bus|J_{hub}) = \frac{\exp\,(V_{car-bus,i}^{hub})}{\sum_{(m1-m2)\in J_{hub}} \exp\left(V_{m1-m2,i}^{hub}\right)}, \qquad \forall i \in I \tag{3.9}$$

$$P_i(hub|J) = \frac{\exp\left(V_{hub,i}\right)}{\sum_{j\in J} \exp\left(V_{j,i}\right)}, \qquad \forall i \in I \tag{3.10}$$

$$V_{hub,i} = \beta * \text{In}\left(\sum_{j \in J_{hub}} \exp\left(V_{j,i}^{hub}\right)\right) + asc_{hub,i}, \qquad \forall i \in I \tag{3.11}$$

where J is the upper-level alternative set including six initial modes plus one general mode with the hub, J_{hub} is the lower-level alternative set including all available multimodal trips using the hub. $P_i(car - bus|J_{hub})$ denotes the probability of choosing the 'Car—Hub—Bus' option in J_{hub} which can be calculated using the pre-trained model coefficients. $P_i(hub|J)$ denotes the probability of choosing the option 'Hub' among the upper-level alternative set, depending on $V_{hub,i}$ that is not included in the pre-trained model. Therefore, we introduce β for the expected utility given J_{hub} and $asc_{hub,i}$ for the mode specific constant of using the hub.

To be more specific, we considered a general β and population segment-specific constants $asc_{hub,notlowincome}$, $asc_{hu\ \ ,lowincome}$, $asc_{hub,senior}$, $asc_{hub,student}$. For instance, the utility of a student using the hub to travel from origin block group u to destination block group w is defined in Eq. (3.12).

$$V_{hu\ \ ,uw,student} = \beta * \text{In}\left(\sum_{j \in J_{hub}} \exp\left(V_{j,uw,student}^{hub}\right)\right) + asc_{hub,student} \tag{3.12}$$

where agent i is decomposed into trip OD pair and population segment, and with β and $asc_{hub,student}$ the probability $P_{uw,student}(car - bus|J)$ can be predicted. With such an initial setting, additional information was required as a supplementary to the pre-trained model:

- We need to define the set of OD pairs uw that we are interested in. We assumed that multimodal trips with the hub would be considered only if they would not increase the total trip length too much. To this end, potential trips that could be impacted by the hub should be identified first, as well as the travel time and cost of these multimodal trips.
- We need to calibrated five hub-related coefficients, including β, $asc_{hub,notlowincome}$, $asc_{hub,lowincome}$, $asc_{hub,senior}$, $asc_{hu\ \ ,student}$. These coefficients can only be calibrated with ground truth hub usage data.

3.2.2. Step 1: Generating Potential Trips and the New Alternative Set

The first step was to identify potential trips with multimodal trip options using the mobility hub. In this step, we first identified all potential trip OD pairs that might by influenced by the two mobility hubs using Replica's synthetic trip data in 2023 Quarter 2 (the latest version of data available). Let 'OD' denote the centroid distance between trip origin and destination block group, 'OH' denote the centroid distance between trip origin and mobility hub block group, and 'HD' denote the centroid distance between the mobility hub and trip destination block group. An OD pair was identified as a potential trip OD pair if ('OH'+'HD'<threshold * 'OD') or ('OH' + 'HD' < 'OD' + 1km), which means using the mobility hub should not increase the total trip length too much. A threshold was required for the identification, which was assumed to be 1.2 in **Figure 3.7** and was rounded up from our survey data indicating 1.18.

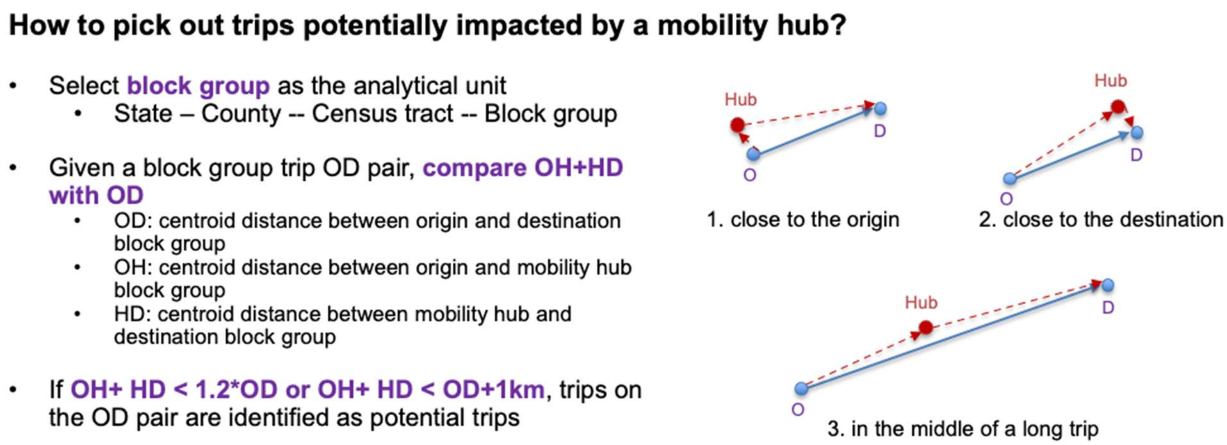


Figure 3.7. The identification of potential trip OD pairs

Based on the location of the mobility hubs, we draw a 10 km buffer to include all census block groups as our study area, and identified potential trip OD pairs among all trips that start or end in these block groups. **Figure 3.8** shows the study area (grey zones) and potential OD pairs for impact assessment. Within a 5 km buffer of the UAlbany Downtown Campus hub (zones with red edges), there were 98,438 residents, not-low-income population accounted for 48.60%, low-income population accounted for 8.43%, senior population accounted for 13.55%, student population accounted for 29.41%. Within a 5 km buffer of the Downtown Cohoes hub (zones with red edges), there were 50,045 residents, not-low-income population accounted for 54.12%, low-income population accounted for 5.91%, senior population accounted for 16.74%, student population accounted for 23.22%. Moreover, the mobility hub in UAlbany Downtown Campus had 20,511 potential trips per weekday, 11,468 potential trips per weekend, and the mobility hub in Downtown Cohoes had 5,470 potential trips per weekday, 5,681 potential trips per weekend. For more details such as the proportion of trips made by each population segment and the mode share, please refer to **Appendix A**.

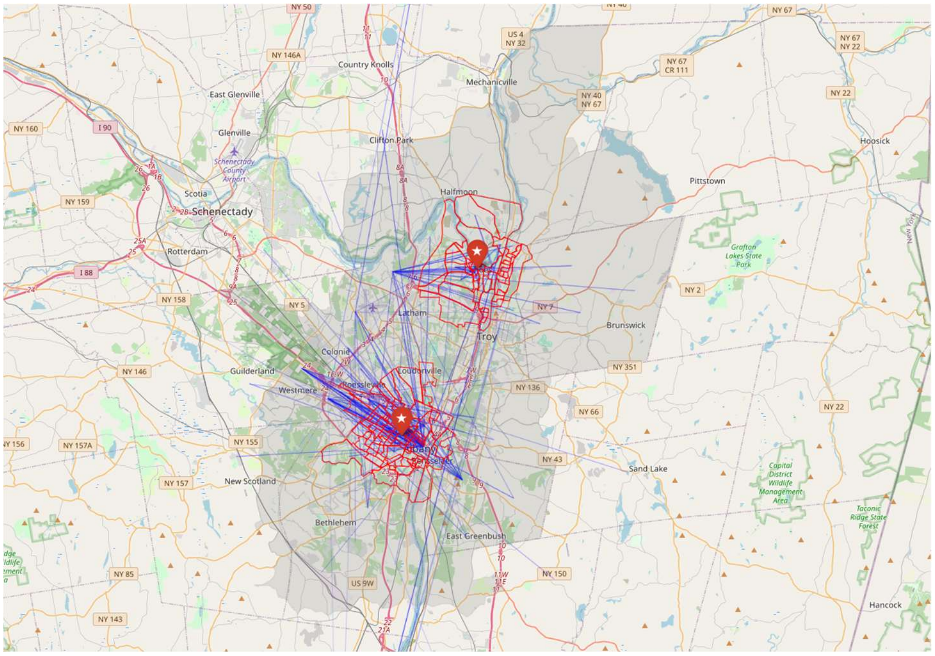


Figure 3.8. Study area and potential trip OD pairs for impact assessment

We then retrieved the travel time and distance of these OD pairs from Google Direction API, by modes including driving, transit, biking, and walking. For each OD pair, travel time (in minutes) and distance (in meters) were retrieved for ‘OD’, ‘OH’, and ‘HD’. **Figure 3.9** shows a sample of the dataset retrieved from Google Direction API. Another issue is that both Replica’s data and Google API do not contain trip monetary cost. To this end, we inferred the costs for each trip based on information such as trip mode, trip length, and trip origin & destination. **Appendix B** shows how we infer trip monetary cost.

origin_bgrp	destination_bgrp	lat_o	lng_o	lat_d	lng_d	lat_hub	lng_hub	mode	distance_1	duration_1	distance_2	duration_2
360010011001	360010146151	42.652410	-73.750938	42.695518	-73.914125	42.660232	-73.771926	driving	2101	5.800000	13573	21.933333
360010011001	360010146151	42.652410	-73.750938	42.695518	-73.914125	42.660232	-73.771926	transit	2518	21.133333	38698	98.400000
360010011001	360010146151	42.652410	-73.750938	42.695518	-73.914125	42.660232	-73.771926	bicycling	2498	14.716667	15722	49.316667
360010011001	360010146151	42.652410	-73.750938	42.695518	-73.914125	42.660232	-73.771926	walking	2040	31.250000	14950	202.916667
360010003003	360010146151	42.677892	-73.759640	42.695518	-73.914125	42.660232	-73.771926	driving	3872	8.716667	13573	21.933333

Figure 3.9. A sample dataset retrieved from Google Direction API

Based on the survey data we considered 16 available mode combinations at the Cohoes hub, and 10 available mode combinations at the UAlbany hub (since DRIVE is not available there), which are shown in **Figure 3.10**. These mode options formed a *sub alternative* set labeled as trips within the mobility hub alternative as a nested structure.

```
['Bus-Bus',
 'Bus-Car Share (DRIVE)',
 'Bus-Walking',
 'Bus-CYCLE! Bike Share',
 'Car Share (DRIVE)-Bus',
 'Car Share (DRIVE)-Walking',
 'Car Share (DRIVE)-CYCLE! Bike Share',
 'Car-Bus',
 'Car-Walking',
 'Car-CYCLE! Bike Share',
 'CYCLE! Bike Share-Bus',
 'CYCLE! Bike Share-Walking',
 'CYCLE! Bike Share-Car Share (DRIVE)',
 'Walking-Car Share (DRIVE)',
 'Walking-CYCLE! Bike Share',
 'Walking-Bus']
```

Downtown Cohoes hub

```
['Bus-Bus',
 'Bus-Walking',
 'Bus-CYCLE! Bike Share',
 'Car-Bus',
 'Car-Walking',
 'Car-CYCLE! Bike Share',
 'CYCLE! Bike Share-Bus',
 'CYCLE! Bike Share-Walking',
 'Walking-CYCLE! Bike Share',
 'Walking-Bus']
```

UAlbany Downtown Campus hub

Figure 3.10. Multimodal options available at the mobility hubs

3.2.3. Step 2: Calibrating Mobility Hub-related Coefficients with Ground Truth Data

The second step was to calibrate hub-related coefficients for calibration. The proportion of potential trips using the hub is essential for calibrating hub-related coefficients. For the Downtown Cohoes hub, we knew: (1) there were 28 trips/month using DRIVE in October (according to the app backend data); (2) the proportion of trips using DRIVE was around 15% (according to our onsite survey), and; (3) the number of potential trips related to the hub was 5,488 trips/day (according to a weighted weekday and weekend trips in the Step 1). Therefore, there should be (28/30/0.15 = 6.22) trips/day using the Downtown Cohoes hub, accounting for (6.22/5488 * 100% = 0.1134%) of the potential trips. Since the survey has been conducted for two months, the rough sample rate at the Cohoes hub was (18/6.22/60 * 100% = 4.82%), which make sense according to our empirical knowledge. As for the UAlbany hub, since DRIVE backend data was not available, we assumed the same sample rate, which results in (22/60/4.82%=7.60) trips/day, accounting for (7.60/17750 * 100% = 0.0428%) of the potential trips. Therefore, for each weekend there should be (0.0428% * 20511 = 8.82) trips using the UAlbany hub and (0.1134% * 5470 = 6.20) trips using the Cohoes hub.

We used the Nelder-Mead Simplex algorithm to calibrate coefficients in Python. The cost function was the squared distance between expected and predicted hub trips. The algorithm converged after 375 iterations and 1.6 seconds. Since the model was trained for weekdays, we only used weekday potential trips. The results are shown in **Table 3.1**.

Table 3.1. Calibrated hub-related coefficients

β	$asc_{hub,notlowincome}$	$asc_{hub,lowincome}$	$asc_{hub,senior}$	$asc_{hub,student}$
0.1237	-5.2682	-6.9988	-3.276	-4.7021
Trip proportion with the hub in UAlbany Downtown Campus				
Ground truth: 0.0428%	Predicted: 0.0430%			
Trip proportion with the hub in Downtown Cohoes				
Ground truth: 0.1134%	Predicted: 0.1003%			

3.2.4. Results Validation

To validate our calibration results, we selected potential trips with origins or destinations close to the two mobility hubs (within 1 km), predicted ridership with the calibrated model, and referred to bus and bike count data in Section 3.1.2. **Table 3.2** shows the ground truth and predicted bus trips per weekday. It is noted that our initial coefficients fitted UAlbany Downtown Campus well but fit Downtown Cohoes poorly, which might be because our pre-trained model (using data in 2019) underestimated the number of bus trips. Therefore, we tweaked the mode specific constant of transit by adding a general value of 2.17 (to capture the increase of transit ridership), resulting in an adjusted prediction that was much closer to the ground truth. Though the model predicted fewer bus trips compared to the ground truth, the difference values were generally acceptable (three of them within 10%, one around 20%). The adjustment of transit constant brought a slight increase of predicted trips using mobility hub from 0.1003% to 0.1128%, which was closer to the targeted value (0.1134%).

Table 3.2. A comparison of ground truth and predicted bus trips

	Ground truth	Predicted	Difference
Bus pick-up trips (UAlbany)	267/weekday	213/weekday	-20.2%
Bus drop-off trips (UAlbany)	192/weekday	175/weekday	-9.1%

Bus pick-up trips (Cohoes)	234/weekday	19/weekday	-91.8%
Bus drop-off trips (Cohoes)	220/weekday	16/weekday	-92.7%
Bus pick-up trips (*Cohoes-adjusted*)	234/weekday	221/weekday	-5.5%
Bus drop-off trips (*Cohoes-adjusted*)	220/weekday	204/weekday	-7.3%

As for bike trips, we did not have additional information to separate trips using private bikes and trips using CYCLE!, so we listed the ground truth trip counts using CYCLE!, predicted number of bike trips, and the estimated proportion of bike trips using CYCLE! (**Table 3.3**). It shows that the estimated proportion was between 3.7% to 7.8% and the proportion in UAlbany was higher than in Cohoes, which aligned with our empirical knowledge.

Table 3.3. A comparison of ground truth and predicted bike trips

	Ground truth (CYCLE!)	**Predicted (all bike trips)**	**Estimated proportion**
Bike started trips (UAlbany)	2.47/day	42 trips/weekday	5.9%
Bike ended trips (UAlbany)	2.73/day	33 trips/weekday	8.3%
Bike started trips (Cohoes-adjusted)	0.49/day	13 trips/weekday	3.8%
Bike ended trips (Cohoes-adjusted)	0.44/day	12 trips/weekday	3.7%

3.3. Impact Assessment with the Calibrated Model

Once the model has been calibrated, the impact assessment was quite straightforward. For the impact assessment we mainly consider four aspects:

- **Mode shift:** a trip that uses a hub now was assumed to have two modes (before and after reaching the hub) compared to a single mode trip before. The count data was used to calibrate alternative specific constants for choosing a hub-based multimodal trip, and for the choice of the modes leading to and from the hub. We then used the updated models to extrapolate to a population level to quantify expected changes in ridership.
- **Reduced VMT:** we retrieved the modal distances using Google Direction API for every motorized, non-transit option. This gave us the before and after comparison of VMT.
- **Reduced carbon emissions:** we used EPA numbers to convert the VMT to average emissions, which was around 400 grams per private vehicle per day.

(https://www.epa.gov/greenvehicles/tailpipe-greenhouse-gas-emissions-typical-passenger-vehicle)

- **Increase of consumer surplus:** the increase of consumer surplus per trip with the mobility hub is defined in Eq. (3.13). The coefficient of trip cost was used to transfer consumer surplus into dollars per trip.

$$\theta_{cost,i}\left(\mathrm{In}\left(\sum_{j\in J}\exp(V_{j,i})\right)-\left(\sum_{j\in J, j\ not\ in\ J_{hub}}\exp(V_{j,i})\right)\right),\qquad \forall i\in I \tag{3.13}$$

4. Mobility Hub Impact Assessment

We separated the impacts of the UAlbany Downtown Campus and Downtown Cohoes hubs by assuming they did not influence each other given their distant locations. We focused on the potential trips identified in Section 3.2.2, which was further separated into direct trips (trips using one of the initial modes) and multimodal trips (trips using one of the mode transfers in the mobility hub). Mode shift, VMT and carbon emissions, and change of consumer surplus were predicted using our calibrated model. Moreover, we extended our discussion from consumer surplus to broader application scenarios of our methodology.

4.1. Impacts on Mode Shift

4.1.1. The Mobility Hub in UAlbany Downtown Campus

Table 4.1 shows the predicted mode shift of potential trips after the demonstration of the mobility hub in UAlbany Downtown Campus. In general, 0.043% of the potential trips were multimodal trips with a mode transfer in the mobility hub, resulting in 8.83 trips/weekday. Most of these trips were shifted from direct trips using private auto (5.94 trips/day). As for these multimodal trips, we split the mode combination (e.g., a 'Car—Hub—Bus' trip accounts for two half trips, one with private auto and another with public transit) and calculated the mode share. The results shows that 53.50% of them used bus, 19.47% of them used private car, 17.89% of them used bike or CYCLE!, and 9.14% of them chose to walk. The increase of bus ridership was 4.72 - 0.27 = 4.45 trips/day.

Table 4.1. Impacts on the mode shift of potential trips (UAlbany Downtown Campus)

	Trips/day (before)	Trips/day (after)	Trips/day (changed)	Proportion (before)	Proportion (after)	Proportion (changed)
Direct trips without using the mobility hub						
Private_auto	13,798	13,792	-5.94	67.27%	67.24%	-0.0491%
Transit	634.8	634.5	**-0.27**	3.10%	3.09%	-0.0023%
On_demand_auto	481.6	481.3	-0.21	2.35%	2.35%	-0.0017%
Biking	151.0	150.9	-0.06	0.74%	0.74%	-0.0005%

Walking	1,785.5	1,784.3	-0.77	8.71%	8.70%	-0.0064%
Carpool	3,660.0	3,658.6	-1.57	17.84%	17.84%	-0.0130%
Total	20,511	20,502	8.83	100%	99.95%	-0.0043%
Multimodal trips using the mobility hub						
Bus (Transit)	--	**4.72**	--	--	53.50%	--
Car (Private_auto)	--	1.72	--	--	19.47%	--
DRIVE (Carpool)	--	0	--	--	0	--
Biking & CYCLE!	--	1.58	--	--	17.89%	--
Walking	--	0.81	--	--	9.14%	--
Total	--	8.83	--	--	100%	--

4.1.2. The Mobility Hub in Downtown Cohoes

Table 4.2 shows the predicted mode shift of potential trips after the demonstration of the mobility hub in Downtown Cohoes. In general, 0.1128% of the potential trips were multimodal with a transfer in the mobility hub, resulting in 6.17 trips/day. About half of these trips were shifted from direct trips with private auto (-3.46 trips/day). As for these multimodal trips, 49.41% of the travelers used bus, 14.44% of the travelers used private car, 18.82% of the travelers used car share (DRIVE), 8.13% of the travelers used bike or CYCLE!, and 9.19% of the travelers chose to walk. The increase of bus ridership was 3.05 - 0.53 = 2.52 trips/day.

Table 4.2. Impacts on the mode shift of potential trips (Downtown Cohoes)

	Trips/day (before)	Trips/day (after)	Trips/day (changed)	Proportion (before)	Proportion (after)	Proportion (changed)
Direct trips without using the mobility hub						
Private_auto	3,069.5	3,066.0	-3.46	56.12%	56.05%	-0.0633%
Transit	467.12	466.59	**-0.53**	8.54%	8.53%	-0.0096%
On_demand_auto	32.48	32.45	-0.04	0.59%	0.59%	-0.0007%
Biking	20.65	20.63	-0.02	0.38%	0.38%	-0.0004%
Walking	910.59	909.57	-1.03	16.64%	16.63%	-0.0188%
Carpool	969.66	968.57	-1.09	17.73%	17.71%	-0.0200%

Total	5,470	5,464	-6.17	100%	99.89%	-0.1128%
Multimodal trips using the mobility hub						
Bus (Transit)	--	**3.05**	--	--	49.41%	--
Car (Private_auto)	--	0.89	--	--	14.44%	--
DRIVE (Carpool)	--	1.16	--	--	18.82%	--
Biking & CYCLE!	--	0.50	--	--	8.13%	--
Walking	--	0.57	--	--	9.19%	--
Total	--	6.17	--	--	100%	--

4.2. Impacts on VMT and Carbon Emission

4.2.1. The Mobility Hub in UAlbany Downtown Campus

Table 4.3 shows the impacts of UAlbany Downtown Campus hub on VMT and carbon emission, in which the 'VMT (before)' column shows the VMT before the demonstration of the mobility hub, the 'VMT (after-direct)' column shows the VMT brought by direct trips after the demonstration of the mobility hub, and the 'VMT (after-multi)' column shows the VMT brought by multimodal trips after the demonstration of the mobility hub. In general, the mobility hub brought a car VMT reduction of 55.83 miles per day (20.37 miles per year), reducing 22.33 kilograms of carbon emission per day (8.15 metric tons per year).

Table 4.3. Impacts on the VMT and carbon emission (UAlbany Downtown Campus)

	VMT (before)	VMT (after)	VMT (changed)	Reduced Carbon Emission
Counting per day				
Private_auto	100,550 miles	100,508 miles	-41.57 miles	-16.63 kilograms
Carpool	24,509 miles	24,495 miles	-14.26 miles	-5.70 kilograms
Total vehicles	125,059 miles	125,003 miles	**-55.83 miles**	**-22.33 kilograms**
Counting per year				
Private_auto	$3.670*10^7$ miles	$3.668*10^7$ miles	-15.17 thousand miles	-6.07 metric tons
Carpool	$8.946*10^6$ miles	$8.941*10^6$ miles	-5.20 thousand miles	-2.08 metric tons

Total vehicles	$4.565*10^7$ miles	$4.563*10^7$ miles	**-20.37 thousand miles**	**-8.15 metric tons**

4.2.2. The Mobility Hub in Downtown Cohoes

Table 4.4 shows the impacts of Downtown Cohoes hub on VMT and carbon emission. In general, the mobility hub brought a car VMT reduction of 36.06 miles per day (13.16 thousand miles per year), reducing 14.45 kilograms of carbon emission per day (5.27 metric tons per year).

Table 4.4. Impacts on the VMT and carbon emission (Downtown Cohoes)

	VMT (before)	VMT (after)	VMT (changed)	Reduced Carbon Emission
Counting per day				
Private_auto	28,573 miles	28,536 miles	-36.92 miles	-14.79 kilograms
Carpool	7,311 miles	7,312 miles	+0.86 miles	+0.34 kilograms
Total vehicles	35,884 miles	35,848 miles	**-36.06 miles**	**-14.45 kilograms**
Counting per year				
Private_auto	$1.043*10^7$ miles	$1.042*10^7$ miles	-13.48 thousand miles	-5.39 metric tons
Carpool	$2.669*10^6$ miles	$2.669*10^6$ miles	+0.32 thousand miles	+0.12 metric tons
Total vehicles	$1.310*10^7$ miles	$1.308*10^7$ miles	**-13.16 thousand miles**	**-5.27 metric tons**

4.2.3. Summary of VMT and GHG Emissions Impacts

In total, the two hubs were projected to reduce VMT by (55.83+36.92 = 92.75) vehicle-miles per day, or 33,853 vehicle-miles in a year. The corresponding GHG emissions reduction was (22.33+14.45 = 36.78) kg per day, or 13.42 metric tons of carbon emissions (MTCE) per year, which is similar to the carbon footprint of two average households. *In other words, there is potential for each mobility hub installment to reduce GHG emissions equivalent to one household's worth each, although effectiveness varies by case.*

4.3. Impacts on Consumer Surplus and More Scenarios

4.3.1. Change of Consumer Surplus under the Context of Hub Service Fee

Table 4.5 shows the increase of consumer surplus brought by the two mobility hubs, which was defined in Section 2.2.4. In general, the hub in UAlbany Downtown Campus brought an increase of consumer surplus of $0.1950 for each potential trip, and with 20,511 trips/day the total increased dollar amount equals to $4,000/day. The hub in Downtown Cohoes brought an increase of consumer surplus of $0.3185 for each potential trip, and with 5.470 trips/day the total increased dollar amount equals to $1,742/day. The interpretation is that having the mobility hub created economic value for travelers defined within the vicinity of the hubs indicated in **Figure 3.8**, equivalent to that dollar amount for each of their trips whether or not they used the hub.

Table 4.5. Impacts on consumer surplus of potential trips

	UAlbany Downtown Campus	Downtown Cohoes
Change of consumer surplus	+$0.1950/trip	+$0.3185/trip
Total number of trips	20,511 trips/day	5,470 trips/day
Total dollar amount	$4,000/day	$1,742/day

However, the total predicted revenue collected by the UAlbany hub (only including bus and DRIVE, since we don't have the information of how many bike trips used CYCLE!) is only $34.49/day or $1,035/month, and the total predicted revenue collected by the UAlbany hub is only $24.44/day or $733/month. The main reason for this huge gap is that the proportion of trips using the mobility hub is quite low (about 0.1%), which could be attributed to two aspects:

- Currently there are only two mobility hubs implemented, resulting in limited convenience brought by multimodal trips in terms of saved travel time and available mode transfers. In that case, the performance of mobility hub service is not that attractive compared with driving private vehicles.
- Given that the CDTA service fare for bus line is generally $1.50 per trip (without any discount considered), the added value per trip is around $0.20-$0.30, which is at about one fifth to one seventh of the full bus fare. Considering that user preferences are quite diverse, various pricing policies should be designed to balance the added value and charged fare per trip.

4.3.2. A Single Scenario: What if There Was a Discount in Using the Hub

Besides assessing the impacts of current pricing policies of the two mobility hubs, our calibrated model can assess impacts under new scenarios. To showcase the potential of our methodology, this section applies our model to a simple scenario in which bus service is free for trips using the mobility hub. **Table 4.6** summarizes the change of mode share, VMT, carbon dioxide emission, and consumer surplus, and the total revenue collected at the hub. We saw a total increase of 3.12 trips/day using the mobility hub (2.33 trips/day for the UAlbany hub, 0.79 trips/day for the Cohoes hub), resulting in a further increase in bus ridership in the hub (3.26+1.67 = 4.93) trips/day, a further reduction in VMT (23542-20377+19966-13475 = 9,656 vehicle-miles/year) and carbon emission (9.42-8.15+7.99-5.27 = 3.99 tons/year), a further increase in consumer surplus (about $0.06/trip). However, this was at the cost of losing total revenue of $34.49 - $15.73 + $24.44 - $12.45 = $30.75 per day.

Table 4.6. Change of impacts if bus is free at the mobility hub

	Trips/day (before)	Trips/day (after)	Trips/day (changed)	Proportion (before)	Proportion (after)	Proportion (changed)
Multimodal trips using the mobility hub (UAlbany Downtown Campus)						
Bus (Transit)	4.72	7.98	+3.26	53.50%	71.51%	+18.01%
Car (Private_auto)	1.72	1.40	-0.32	19.47%	12.57%	-6.90%
DRIVE (Carpool)	0	0	0	0	0	0%
Biking & CYCLE!	1.58	1.15	-0.43	17.89%	10.26%	-7.63%
Walking	0.81	0.63	-0.18	9.14%	5.66%	-3.48%
Total	8.83	11.16	+2.33	100%	100%	0%
Impact assessment (UAlbany Downtown Campus)						
	Before			**After**		
Reduced VMT	20,377 vehicle-miles/year			23,542 vehicle-miles/year		
Reduced C02 emission	8.15 tons/year			9.42 tons/year		
Increased consumer surplus	$0.1950/trip			$0.2503/trip		
Total hub revenue	$34.49/day			$15.73/day		
Multimodal trips using the mobility hub (Downtown Cohoes)						

Bus (Transit)	3.05	4.72	+1.67	49.41%	67.87%	+18.46%
Car (Private_auto)	0.89	0.56	-0.33	14.44%	7.98%	-6.46%
DRIVE (Carpool)	1.16	0.86	-0.30	18.82%	12.31%	-6.51%
Biking & CYCLE!	0.50	0.34	-0.16	8.13%	4.96%	-3.17%
Walking	0.57	0.48	-0.09	9.19%	6.89%	-2.30%
Total	6.17	6.96	+0.79	100%	100%	0%

Impact assessment (Downtown Cohoes)

	Before	**After**
Reduced VMT	13,475 vehicle-miles/year	19,966 vehicle-miles/year
Reduced C02 emission	5.27 tons/year	7.99 tons/year
Increased consumer surplus	$0.3185/trip	$0.3746/trip
Total hub revenue	$24.44/day	$12.45/day

4.3.3. Proposed Scenarios for the Future Work

The key to the success of mobility hubs is finding the best site location, hub density, and pricing policy to encourage more travelers to use them in a broader range. This requires behavioral simulations under a series of scenarios such as what would be the impact on mobility hubs if there were a discount on the hub service fare? Given 10 candidate sites to build new mobility hubs, how to rank them? If there were enough mobility hubs, could a fare reduction or fare free policy be supplemented by revenues contributed by partner mobility providers?

Our methodology has the potential to answer these questions. Using existing bus terminal locations, we can quickly cut out potential trips that might be impacted, calibrate hub-related coefficients for new mobility hubs (or use current coefficients if we do not have additional information), and then calculate the predicted benefits. We may even do this for a sample of 30-50 sites, and then build a regression model off more accessible public data to then apply this more easily across NYS at a much larger scale. To be more specific, future scenarios can include:

- Analyzing potential new sites using the demand model to quantitively rank locations for different objectives (like equity, VMT reduction, Ridership, etc.).

- Analyzing fare discount policy impact on ridership increase to mobility partners and using that to determine minimum number of additional hubs that would allow mobility partners to cover fare free for transit.
- Analyzing fare bundling with partners to see what discounts can be supported by the increase in demand for transit and partner(s).
- Optimizing total revenue for the partners by setting a bundle fare or transit fare price.

5. Conclusion & Future Work

This report focuses on the impact assessment of two mobility hubs built in UAlbany Downtown Campus and Downtown Cohoes.

According to the survey data, 52.23% of the trips are made by not-low-income population, 8.90% of the trips are made by low-income population, 17.49% of the trips are made by seniors, and 21.37% of the trips are made by students. Our calibrated model results showed that the UAlbany hub introduced 8.83 multimodal trips per day (accounting for 0.0430% of the potential trips) and the Cohoes hub introduced 6.17 multimodal trips per day (accounting for 0.1003% of the potential trips). For each weekday the UAlbany hub brought an increase of 4.45 bus trips, a reduction of VMT of 55.83 miles, a reduction of 22.33 kilograms of CO_2 emission, and an increase of consumer surplus of $0.1950 per trip. For each weekday Cohoes hub brought an increase of 2.52 bus trips, a reduction of VMT of 36.06 miles, a reduction of 14.45 kilograms of CO_2 emission, and an increase of consumer surplus of $0.3185 per trip. In a hypothetical scenario in which the bus service is free for trips using the mobility hub, we showed that there would be a further increase of bus trips (4.93 trips/day), a further reduction in VMT (9,656 vehicle-miles/year), a further reduction in carbon emission (3.99 metric tons/year), and a further increase in consumer surplus ($0.06/trip) at the cost of losing total revenue collected at the hubs ($30.75/day).

The results above are based on our calibrated model given available data at this stage. In the future, many other datasets can help better fit our model, including but not limited to: (1) detailed time and cost of trips with mode transfers at the mobility hubs (instead of retrieving from Google Direction API that is a rough approximation); (2) multi-source ground truth data to validate our model results, such as daily bike trips (including with CYCLE! and private vehicles), monthly mode share at the mobility hub, or total trips using the mobility hub per year. Moreover, we can train our mode choice model with the latest dataset (April to June 2023) on both weekday and weekend, which could also help to increase the prediction accuracy, and; (3) more responses (around 100) of the survey to make it feasible to calibrate a separate mode choice model (in that case the calibration of hub-related coefficients would be more stable).

The future of mobility hubs should be more than the two demonstrated ones. The key to the success of mobility hubs is finding the best site location, hub density, and pricing policy to encourage more travelers to use them in a broader range. Since the pre-trained model is for the whole New York State, our methodology is scalable to any number of mobility hubs implemented in the New York State. Once our model became stable after fitting enough survey responses and app backend data, we only need available mode options at each hub for impact assessment since statewide trip OD pairs and travelers' preferences are already known. The only assumption we need to make is that these mobility hubs are distant and independent to each other. Moreover, the calibrated model in this report can be applied to many future works. For instance, potential new sites can be ranked quantitively using the model for different objectives (like equity, VMT reduction, Ridership, etc.). Impact of fare discount policy can be predicted and total revenue for hub partners can be optimized.

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Appendix A. Details of Potential Trips

Table A.1. Details of potential trips related to UAlbany Downtown Campus

	Low-income	Not low-income	Senior	Student	Total
Trips on weekdays					
# Trips per day	757	17,190	102	3,016	21,065
% Private Auto	**46.76%**	**72.74%**	**85.29%**	**47.02%**	**68.18%**
% Public Transit	25.76%	3.57%	4.90%	1.49%	4.07%
% On-demand Auto	0.66%	3.70%	1.96%	0.99%	3.19%
% Biking	2.38%	0.47%	0%	1.09%	0.63%
% Walking	4.10%	4.74%	0%	37.93%	9.45%
% Carpool	20.34%	14.78%	7.84%	11.47%	14.47%
Trips on weekends					
# Trips per day	502	9,473	50	1,443	11,468
% Private Auto	30.68%	**60.32%**	**58.00%**	**54.89%**	**58.33%**
% Public Transit	15.34%	1.67%	4.00%	0.55%	2.14%
% On-demand Auto	0.20%	2.64%	0%	1.04%	2.32%
% Biking	3.19%	0.21%	0%	1.39%	0.49%
% Walking	18.33%	4.24%	0%	14.62%	6.15%
% Carpool	**32.27%**	30.92%	38.00%	27.51%	30.58%

Table A.2. Details of potential trips related to Downtown Cohoes

	Low-income	Not low-income	Senior	Student	Total
Trips on weekdays					
# Trips per day	160	4,991	247	467	5,865
% Private Auto	**50.62%**	**72.89%**	**83.81%**	7.71%	**67.55%**
% Public Transit	0%	1.20%	0%	1.28%	1.13%
% On-demand Auto	0%	0.58%	0%	0%	0.49%
% Biking	0%	0.10%	0%	2.78%	0.31%
% Walking	0%	10.94%	8.50%	**73.66%**	15.53%
% Carpool	49.38%	14.29%	7.69%	14.56%	14.99%
Trips on weekends					
# Trips per day	72	5,371	238	0	5,681
% Private Auto	29.17%	**59.13%**	**63.87%**	-	**58.95%**
% Public Transit	0%	0.65%	0%	-	0.62%
% On-demand Auto	0%	0.45%	0%	-	0.42%
% Biking	0%	0.37%	0.42%	-	0.37%
% Walking	20.83%	10.69%	8.40%	-	10.72%
% Carpool	**50.00%**	28.71%	27.31%	-	28.92%

Appendix B. Inferring Trip Monetary Cost

Table B.1. Monetary cost inference for private auto, public transit, and Car Share (DRIVE)

1.Private auto		
Item	**Unit price**	**Description**
Cost per trips	\$0.07/mile	For trips of which the origin and destination are outside of NYC. This is calculated based on 2019 NY gas price (\$2.542/gallon[3]) divided by the average mpg of cars and SUVs (36.33 mpg[4])
2. Public transit		
Item	**Unit price**	**Description**
Cost for seniors	\$0.75/trip	Riders who are 65 or older have a 50% discount.
Cost for students	\$1.5/trip	Students discount
Cost for other population	\$2/trip	Regular bus fee
3. Car share (DRIVE)		
Item	**Unit price**	**Description**
Hourly charge	\$5/hour	An hourly charge for the trip.

[3] https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=emm_epmr_pte_y35ny_dpg&f=m
[4] https://techxplore.com/news/2022-04-vehicles-average-mpg.html, https://www.indyautoman.com/blog/best-mpg-suv, https://nhts.ornl.gov/documentation