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The potential effects of Community Hub for Smart Mobility (CHSM) on travel mode choice for accessing transit: A case study of Austin, TX

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The potential effects of Community Hub for Smart Mobility (CHSM) on travel mode choice for accessing transit: A case study of Austin, TX

by

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Report

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Abstract

The potential effects of Community Hub for Smart Mobility (CHSM) on travel mode choice for accessing transit: A case study of Austin, TX

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The Smart Mobility Hub is part of the Smart Cities movement of creating shared mobility in cities. These hubs allow access for e-mobility with e-scooters, e-bikes, and charging stations to provide micro-mobility to neighborhoods struggling with the first-mile problem of public transit accessibility. Access to modes other than cars can provide services to those without vehicle access and circumvent car dependency's negative externalities by providing a connection point within a community. The case study will focus on creating a base model for Austin's neighborhood, Georgian Acres. The base model will serve to study the hub in an underserved community. Studying the hub's impact could lead to more creation of these hubs within the Austin area to create a network of Smart Mobility Hubs. It is essential to understand the hub's impact on the neighborhood's mobility patterns and the ability to fulfill the goals of creating Smart Cities that focus on shared mobility, accessibility, and sustainability.

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Chapter 1: Introduction

BACKGROUND

The Community Hub for Smart Mobility (CHSM) is an NSF Civic Innovation Challenge Project that aims to help vulnerable and underserved communities by co-creating a hub with multiple transportation options. It addresses the spatial mismatch of where people live and work to create a better-connected network at a community-level. The hub will provide services such as shared micro-transit, including e-scooters and e-bikes, a neighborhood circulator, a ride-hailing service, and public transit. Numerous organizations are part of this project, including the Austin Transportation Department (ATD), the Capital Metropolitan Transportation Authority (Cap Metro), the Austin City Council, Jail to Jobs (J2J), Transit Empowerment Fund (TEF), and faculty at The Urban Information Lab at the University of Texas at Austin. The Georgian Acres hub will pilot the Community Hubs for Smart Mobility concept, which will be scaled up in the long term to benefit communities throughout Austin. This initiative aims to enhance access to public transportation improvements, such as Project Connect, a light rail designed to serve Austin's busiest North-South corridor. By providing connectivity to this rail through micro-mobility and hubs, ridership success can be achieved, and people can be encouraged to choose public transit as a viable option for mobility around Austin. The Community Hub for Smart Mobility will establish access modes to public transit for a neighborhood, thus promoting the sustainability of public transit across the city.

Creation of the Hub

The NSF project's research designer chose the region based on their prior research into the travel patterns of the community, which was conducted through Cap Metro Ridership data. The census tracts chosen were identified as vulnerable to displacement and in a transit desert. Despite being near a transit center, the community could not access public transit fully and safely due to highways bordering the area. After evaluation and community engagement, this area was chosen as a pilot site to implement and test the idea of CHSM to benefit the most underserved transportation system and under-resourced job and housing mismatch (Jiao et al., 2023).

A suitability analysis was conducted to optimize the proximity to population density, available land, and current public transit infrastructure. By considering both transit ridership and land suitability, the Smart Mobility Hub was strategically located near community partners, multi-family and single-family homes, and a park. Figure 1 shows the findings from this suitability analysis to locate the hub based on the parcels available to the city. The hub includes various components, such as a neighborhood circulator bus that operates daily and provides convenient access from homes to the hub. At the hub, seating areas are equipped with solar panel shade systems that generate power, enable phone charging, and provide shaded areas in an otherwise sun-exposed space. Furthermore, Wi-Fi is available. The hub also offers shared bikes and e-scooters at discounted rates to address transportation challenges for first and last-mile journeys.

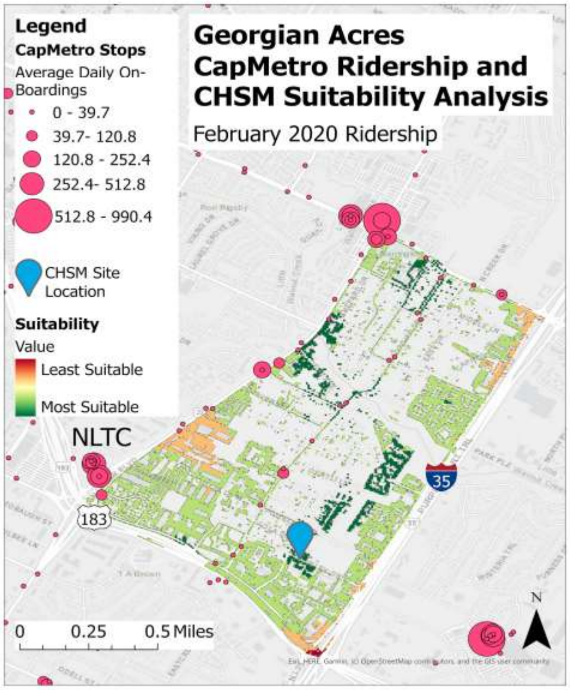


Figure 1: Travel patterns and suitability analysis of Georgian Acres. (*Georgian Acres Community Hub,* 2023)

These circulator buses are crucial to note as Cap Metro expects to expand these neighborhoods' circulator buses throughout 11 neighborhoods in Austin. These neighborhoods are shown in Figure 2, which illustrates the zones where residents can ask for on-demand transit to another area within the zone. Creating a mobility hub similar to the one in Georgian Acres can help enhance the effectiveness of these circulators. The hub can help support public transit riders with first and last-mile accessibility to either their bus stop or their final destination. It can be a place where the on-demand transit service can reliably be if someone needs a safe pick-up or drop-off location. These hubs can work to help integrate the communities into the more extensive Austin Transit Network.

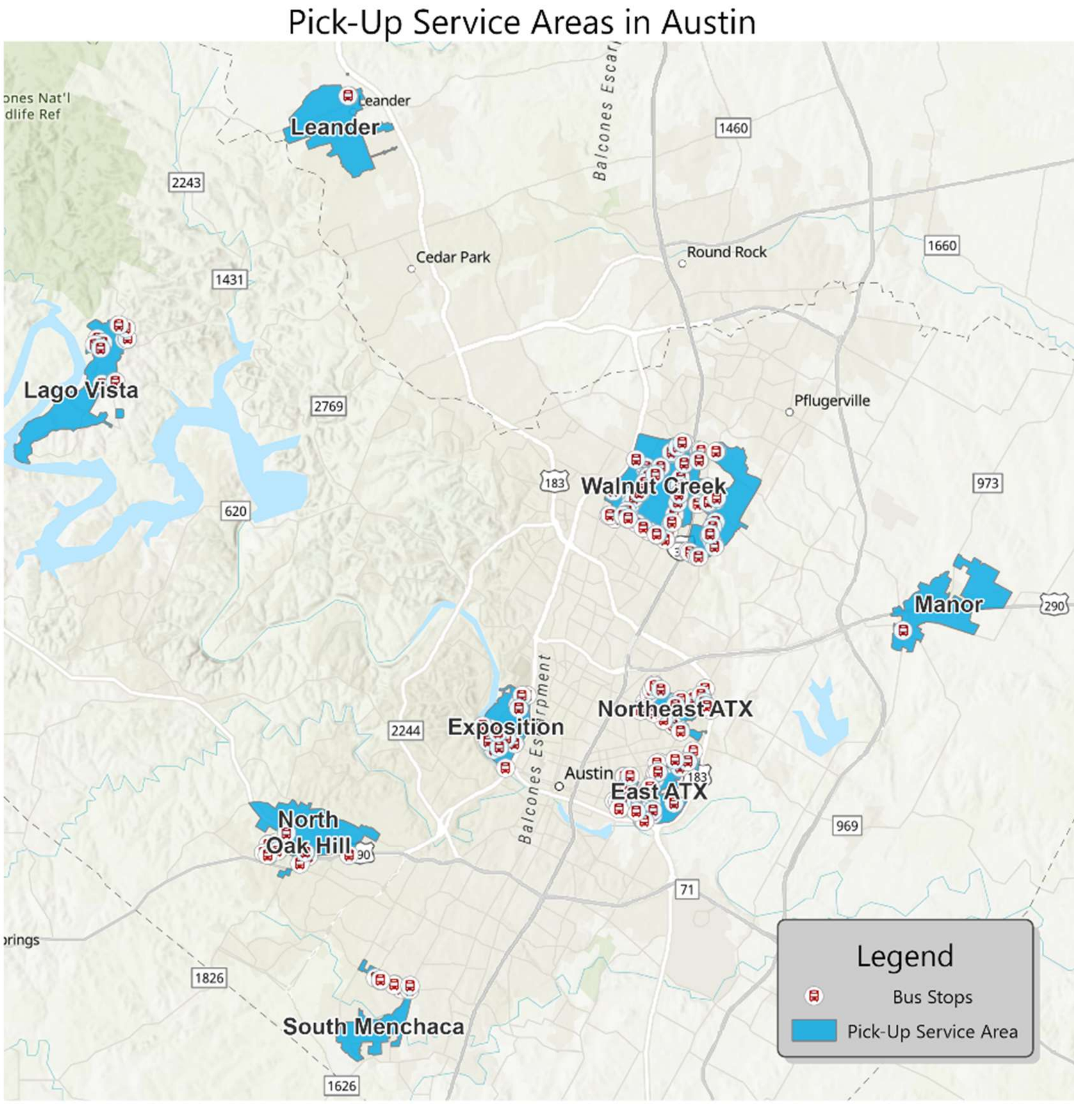


Figure 3: Planned Pick-Up Service Area for Neighborhood Circulators in Austin. (CapMetro, 2020)

Some of the neighborhood zones are existing, recently launched, or upcoming zones based on the latest updates as of this report. These neighborhoods shown in Figure 2 include.

- Existing: Manor, Northeast ATX, East ATX, Exposition, Walnut Creek

- Newest Zones: Dessau (launched 2021), South Manchaca (launched 2021), and North Oak Hill (launched 2021),
- Upcoming: Pflugerville, Lago Vista, Leander

RESEARCH QUESTIONS

This paper will evaluate the potential transportation impacts of the multi-model neighborhood mobility hub in Austin by analyzing the choice behavior of transit access modes in and around the Georgian Acres community. This model can help to evaluate the scalability and transferability of CHSM across Austin and other cities.

1. What are the mode choice behaviors of Georgian Acres before the hub?
    a. What is the mode choice for work commutes in the Georgian Acres community
    b. What is their choice for access mode choice to transit?
2. What is the best framework for modeling the potential mode choice behavior?
3. What is the potential neighborhood's mode choice change due to the hub's implementation?

The Community Hub for Smart Mobility hopes to improve access to public transit for neighborhoods. By developing a base model, we can further assess the scalability of multiple hubs around the city at a community level. The success and research from the Georgian Acres hub could also address similar issues of accessibility to public transit nationwide.

Chapter 2: Literature Review

CURRENT RESEARCH ON ACCESS MODES

A thorough literature review was performed to gain valuable insights into the previous research and modeling of access mode. This paper aims to analyze the findings of these studies to explore the potential application of their methodologies within the scope of the Smart Mobility Hub Project. Our examination will primarily focus on the data collection techniques used, the variables employed for modeling, the modeling methodology itself, and the results obtained from various models.

Research Area

Studying access mode is more intricate than examining primary mode choice, as it involves numerous parameters that can be impacted by the availability of various modes in a particular location (Korf, 1981). Thus, it is essential to delve into this research area when exploring access mode. The research areas that were defined in these studies were determined by these methods:

- Transit stations are categorized by the density and land use of the area the station serves. These stations are categorized into five categories: central city, dense residential, residential with some commercial, primarily commercial with some residential, and sparse residential with undeveloped land (Korf, 1981).
- The number of transit stations observed varies but is often between 2 and 3 and often has their subset of variables that can affect station choice, including distance to station, seat or parking availability, or fare (Chakour, 2014).

Access mode research is dedicated to understanding the average access travel distance to a transit station for a particular transit system, which then defines the study area. For example, the average access travel distance for the eight Bay Area Rapid Transit (BART) stations is between 2.4 and 6.1 km (Korf, 1981). However, depending on the mode, the travel distance can still vary. Analysis of the distance at which someone will be willing to travel for access to the transit system can be used to define the research area. For example, in the BART System, the market area drops after 6.5 km from a station, with 0.8 km characterizing the walking distance to the station (Korf, 1981).

Our research defines the Georgian Acres neighborhood as the area that the Smart Mobility Hub aims to serve. We selected the station's location after considering various factors, such as the lack of transportation options in Austin, the availability of land, and the accessibility of the station to the surrounding community.

Data collection

The samples are random, and between 732 to 3,000 survey respondents. It is recommended to have at least 1,000 observations per 100,000 people "to keep the coefficient estimation error within 25 percent at the 80 percent confidence level" (Tsamboulas, 1992, pg. 232). Surveys found in the research have ranged from on-board surveys to questionnaires asking for stated preferences. These surveys used for the data collection included a passenger profile survey which gives:

- Trip-maker variables such as age, sex, race, education, income, occupational status, household size, and automobile availability

- Trip-related variables such as purpose, origin, origin time, number of traveling companions, and destinations (Korf, 1981).
- Automobile-related variables which include trip time and vehicle occupancy.
- Level of service variables such as access travel time
- Environmental factors such as land use are generated at the Traffic Analysis Zone level.
- Station variables such as the number of stations available based on mode choice (cars offer greater station accessibility)

However, not all of these variables were used or proved to provide much impact on the model. There are some considerations regarding how this data is collected and the available data. Most studies develop aggregate models with socio-demographic information at the postal code level rather than the individual level (Chakour, 2014). There were often difficulties in calculating the level of service variables. However, often travel time skims come from traffic analysis zones (TAZ) (Bergman, 2011). Some studies used Google Maps algorithms to calculate the travel time for each mode. Also, there is reason to consider that many European studies are facilitated in a context where mode share is more diverse than in the United States (Chakour, 2014).

Another aspect to consider in survey analysis is how respondents can have biased responses. Polydoropoulou researched between stated preference (SP) and revealed preferences (RP). Stated preference comes from data collected studying a hypothetical situation where a new mode is presented. Revealed preference comes from authentic trips using on-board surveys or similar, which mitigates the biases that an SP survey could entail. The research pools the RP and SP datasets to provide a more reliable model. This allows for more alternatives for newer mass transit technologies while still representing the decision-making of the area.

Variables Used

The access mode investigated can largely depend on that station of interest. City transit is mainly accessed by walking, while the commuter rail is accessed by no-walking modes. A few access modes used in these studies include.

- Drive-alone (park-and-ride)
- Kiss-and-ride (drop-off)
- Public transit (can be divided into bus and light rail services)
- Carpool
- Walk

Table 1 Polydoropoulou, 2001

Attributes of Main Mode Alternatives	
Bus and Mass Transit Concept	**Car**
Wait time	Driving time
Transfer time	Fuel price
Time riding the vehicle	Parking cost
Number of transfers	Parking search time
Fare	Walk time to/from car
Probability of delay	
Probability of getting a seat	
Attributes of Access Mode Alternatives	
Access Mode to Bus	**Access Mode to Mass Transit**
Walk time	Walk time
Drive time	Drive time
Parking cost	Parking cost
Parking search time	Parking search time
Walk time to/from car	Walk time to/from car or bus

Attribute variables of access mode are different for mass transit and cars. These variables shown in Table 1, socioeconomic variables, and trip characteristics are the most important explanatory variables to model access mode choice (Wen, 2012).

To better understand the accessibility of the station for different modes of transportation, various factors were taken into account. These included the type of station, its volume, parking capacity, and accessibility for automobiles, pedestrians, and buses. Additionally, demographic variables like household income, population density, and racial demographics were considered (Korf, 1981). Demographic variables were classified into 'Yes' or 'No.' For instance, age was divided into middle-aged individuals between 17 and 65, who could move independently, and those who were reliant on others for transportation due to their age. Income was divided into low-income earners earning less than $7000 a year and those earning more. Race was categorized into white and non-white racial groups (Korf, 1981).

MODEL METHODOLOGY

Discrete choice model

A discrete choice model considers every combination of mode choice and other traveling choices as an alternative. The basis for choice modeling is on the maximization of the utility function, which is "a linear function of the attributes of the journey weighted by the coefficients which attempt to represent their relative importance as perceived by the traveler" (Khan, 2007, pg. 19). However, as the number of alternatives increases, each set of alternatives must be analyzed to understand their correlations which makes this approach often not accommodating (Chakour, 2014). Therefore, the nested logit model or segmentation is used to place decisions on a multi-level model and include socioeconomic characteristics that can often be ignored due to the homogenization of the utility function.

Binary vs Multinominal Logit model

Logit models can show more complex travel behaviors, including the utility function. There are binary and multinominal logit models, with the difference being that multinominal logit models have a more extensive set of alternatives. Binary logit models only have two independent alternative options, such as 'car' and 'public transportation.' Therefore, researching correlated modes like 'bus' or 'train' limits the binary logit model. A multinomial logit model (MNL) is a discrete choice model based on more than two traveling alternatives characteristics. However, a limitation is that identical parameters are used for every user when deciding on mode choice without considering individual preferences or the availability of other modes (Wen, 2012; Ferrell, 2015). Both binary and multinominal logit models can be simple or nested. Simple logit models only have one level of alternatives.

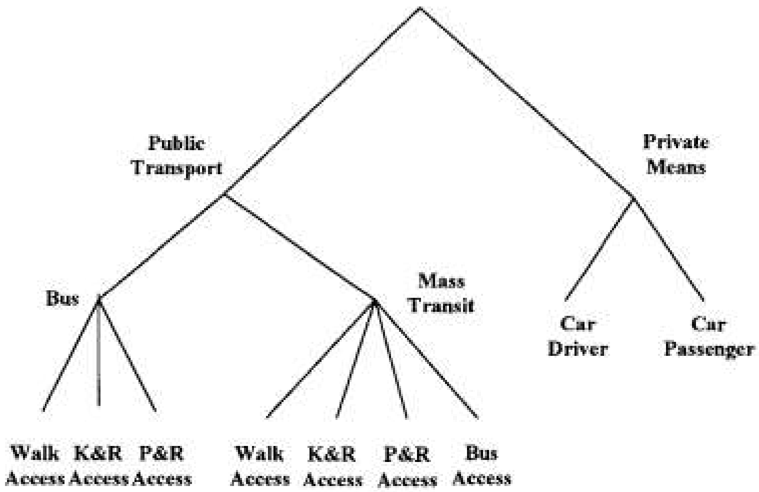


FIGURE 1 SP main mode and access choice model design (K&R = kiss and ride; P&R = park and ride).

Figure 3 (Polydoropoulou, 2001).

Nested-logit model (NL)

A nested-logit model is a common way the simultaneously show two factors in a model. They have an upper level which often represents the primary mode choice, and a lower level represents the access choice to mass transit, as shown in Figure 2 (Polydoropoulou, 2001). Nest logit models allow for correlated modes that the binary logit models do not allow.

Nested-logit models are preferred over multinominal logit models. Due to its ability to differentiate between similar modes of travel and allows for correlation between alternatives (Ferrell, 2015). However, segmentation added to the nested-logit model can improve its goodness of fit (Wen, 2012).

Segmentation

Access mode is often modeled as the first choice in a hierarchical sequence of choices followed by station choice. However, research has attempted "to jointly consider the access mode and station choice decisions without imposing any hierarchy" using a latent segmentation-based approach (Chakour, 2014, pg.226). Segmentation can also help to overcome the shortcomings of a discrete choice model to account for the heterogeneous preferences of users.

There are two main approaches to segmentation, priori segmentation, where the segments are defined by a few attributes, and ad hoc segmentation, where the profiles of segments are determined by a multivariate statistical approach (Wen, 2012). For example, in research studying access mode and station choice, the segmentation process is priori segmentation. There are two segments to consider: Segment 1 – station choice first and access mode second and Segment 2 – access mode first and station choice second. After the access mode is modeled in the first segment, the station choice is decided based on the access mode. The process will help determine the probability of assigning the individual to either of these segments as a function of the various dependent variables (socioeconomic or trip characteristics) (Chakour, 2014). This framework follows the idea that the choices for station and access mode are interconnected and made simultaneously. Other uses for segmentation are in a market segmentation approach which looks at segmenting access mode (car, walking, bus) and trip purpose (work trips and other purposes) to refine the separate individual choice model (Tsamboulas,1992).

For the latent segmentation framework, a binary logit model is used. Comparing models, the latent segment model outperformed the two sequential models based on mode and station choice (Chakour, 2014). Unlike mixed logit models, latent class models can specify the segments' sizes, numbers, and characteristics. In latent class nested logit modeling, the segments are allowed enough flexibility, and the number of segments can be controlled (Wen, 2012).

Overall, Hensher recommends that although more advanced modeling tools exist, mixed and nested logit are still practical travel choice modeling tools when paired with quality data (2007). Considering that access modes have more significant choice sets, a multinominal nested logit model is the approach we are considering for the project.

MODEL TECHNIQUES AND STRUCTURES

$$L_1 = \sum_{m=1}^{M} \log [P(t_m, m)]$$

where,

L	is the likelihood the model assigns to the vector of available alternatives;
M	is the total number of available alternatives;
m	is any alternative present in the set of available alternatives;
t_m	is the mode observed to be chosen in alternative *m*; and
$P(t_m,m)$	is the probability for choosing alternative *m*.

Figure 4 (Khan, 2007)

The maximum likelihood technique is the most common procedure for nested logit modeling (Khan, 2007). Samples of individual mode choice are needed for the maximum likelihood method. Each observed sample will be used to estimate parameters under which conditions are most likely to occur based on the alternatives. The purpose is to maximize the logarithm of L as it monotonically increases. The function is shown above in Figure 2.

Utility Function

The following functions serve as examples of the utility functions used in the Korf study. Various variables must depend on it to increase the likelihood of selecting each mode. These dependent variables include factors such as access distance and access time/cost and perceived variables like auto availability, non-white ethnicity, and low income. To determine if a variable is significant enough to be included in the forecasting model, a t-test statistic can be used. Each mode can have its own set of explanatory variables (Tsamboulas, 1992). However, it is possible to optimize the model by assessing the influence of each variable by running the model and reviewing the t-scores to identify how each variable improves or negatively impacts the model (Korf, 1981).

Table 2: Example utility functions for various modes.

Mode	Utility Function
Bus	$Distance\ Coefficient * Access\ Distance + Time\ Coefficient * Access\ Time + Auto\ Coefficient * Auto\ Availability + Fare * Cost\ Coefficient$
Drive	$Distance\ Coefficient * Access\ Distance + Time\ Coefficient * Access\ Time + Age\ Coefficient * Middle\ Age\ Variable + Cost * Cost\ Coefficient$
Walk	$Distance\ coefficient * Access\ Distance + Auto\ Coefficient * Auto\ Availability$

Model Optimization

Models were optimized by developing the access distance and access time variables independently by mode choice and for the combined model. A unique coefficient was created for modes of drive alone and drop-off to balance the speed at which they travel (Korf, 1981). The station type can also influence the estimated modal speed (e.g., dense areas can create slower speeds). Carpool access times can be more challenging to estimate. Researchers decided to use access time for carpooling, both access distance for driving alone and drop-offs, and access distance for walking (access time was less significant). The vehicle-availability coefficient is a negative influence since bus and walking modes do not require vehicle availability; however, bus fares and walk time can be influential factors.

OTHER FINDINGS

Model Results

Korf discovered that using the access distance and access time models separately resulted in poor predictions, whereas utilizing them in a combined model improved accuracy. The socioeconomic variables had lower t-scores than the level of service variables for access modes showing that they could not ensure modeling a choice as accurately as travel distance and costs, while other studies found that car availability did not have a significant impact on access mode choice (Korf, 1981; Chakour, 2014). However, parking spaces, connecting bus routes, distance to the station, and population density were essential predictors for modeling access mode choice (Bergman, 2011; Chakour, 2014). Studies found that distance mattered greatly because, after a certain distance, people would not use certain mode choices (such as walking) or go to a station (Chakour, 2014). Thus, improving microlevel walkability could help people be more willing to walk to transit stations which helps accessibility and encourages sustainable modes, including transit (Park, 2014).

Scalability

When researching the scalability of these models to other sites, Korf found that each station can create a different importance for each variable. However, research supported that a station-type classification model "can be transferred and comparable to other geographic and socioeconomic areas" (Korf, pg. 33). However, models across these types can be challenging to compare. When developing a model for a new area, the best option is to model an existing station with similar characteristics to the planned new station.

These models first must examine the "various supply and demand scenarios and policies, including concerns such as parking availability and cost, feeder transit fares, and frequency of service" (Korf, 1981, pg.35). The models also need to be sensitive to the supply (e.g., transit service or parking) and demand (e.g., socioeconomic factors) characteristics of the station (Korf, 1981, pg. 35).

Considerations

Most of these research papers try to understand two main logical questions which station to use and how to get to the station (access modes). One factor the researchers saw that impacted station access mode choice was trip purpose. The purpose is a factor we can consider within our research as people may be willing to take other modes for non-work trips versus work trips. Thus, a separate model can be created for each trip's purposes (Tsamboulas, 1992). Also, it might be important to notice the correlations between low-income, non-white, and car availability and understand how they could influence the model depending on different geographic areas. Similarly, since the "distance is calculated from perceived time for each mode," thus, travel time can account for the travel distance (Korf, 1981, pg. 35).

Limitations

Limitations in data are frequently encountered in these studies, particularly when it comes to accessing cost data to evaluate access mode behavior. The availability of seats, parking spots, and other modes of ownership, such as bikes, can also be challenging to collect. While some models aim to incorporate additional access modes, they may struggle to establish revealed preferences due to the newness of these options in the community. As a result, researchers may need to rely on the stated preferences of riders. However, the hub is introducing new mode choices in the Georgian Acres community, which must also be considered when analyzing their access mode preferences.

Chapter 3: Current Mobility Access and Use in Georgian Acres

In this chapter, we delve into the current mobility access and use in the community of Georgian Acres by examining insights from various comprehensive studies. The neighborhood of Georgian Acres presents a unique microcosm of mobility challenges and opportunities, and understanding the dynamics of transportation within this community is essential for fostering a community-based mobility hub. By synthesizing the findings from multiple studies conducted in Austin and Georgian Acres, the prevailing travel patterns, access modes to transit, and the overall mobility behavior of residents will be revealed. Surveys to get the demographic and transit information include:

- American Community Survey: The 2020 American Community Survey (ACS) served as a valuable resource to understand the current demographics of the Georgian Acres community, which was instrumental in shaping the mode choice model to reflect the unique characteristics and needs of the community accurately. By integrating the ACS data, the model could be tailored to align with the diverse demographics of Georgian Acres, ensuring that it captures the essence of the community's mobility behavior and preferences.
- Pre-Hub Survey: Before implementing the hub in the Georgian Acres community, the Pre-Hub Survey was conducted. This survey aimed to gather residents' opinions on the current transit network in their community and identify areas that need improvement. The study also collected data on demographics and trip information. Although 426 people responded to the survey, only 200 were validated with an origin and destination point. As a result, the data collected could not be used for modeling purposes. Nevertheless, the survey provides valuable insights into the community's perception of the hub's implementation and current transit challenges.

- Post-Hub Survey: The Post-Hub Survey was conducted after the hub was built between February 2023 and April 2023 to gather feedback from the community about their experience with the recently built hub and its services. The survey received valid responses from 156 individuals. The questions were similar to those in the Pre-Hub Survey but also asked about the respondents' access mode to public transit.
- Austin Travel Survey (2017): The Austin Travel survey is conducted by the Capital Area Metropolitan Planning Organization (CAMPO). These surveys include household, workplace, and commercial vehicle data collections from Bastrop, Burnet, Caldwell, Hays, Travis, and Williamson Counties. The most recent survey used for this paper began in 2016 and ended in 2018.
- Cap-Metro On-Board Survey: The On-Board Survey by Cap-Metro was conducted in 2015 on the bus to survey passenger trip patterns. The data from this survey includes the access mode to and from the bus stop to understand how people access transit.
- Resampling of the 2017 Austin Travel Survey: The resampled Austin Travel Survey is chosen trips that reflect the demographics of the Georgian Acres neighborhood based on US Census data. In the methodology section, the resampling methodology of the Austin Travel Survey will be further detailed.

Accurately representing the demographics of a specific area is a pivotal aspect of any comprehensive study. In this context, understanding the unique characteristics of the Georgian Acres community was vital in constructing a well-represented model that mirrors the neighborhood's diverse population and mobility patterns. Incorporating the surveys listed, we conducted a thorough descriptive analysis. Through these efforts, a comprehensive understanding of the community's demographics was achieved, ensuring that the sample dataset used for the model accurately reflected the realities of Georgian Acres.

Descriptive Analysis

A descriptive analysis was conducted on the Georgian Acres to understand the current community's demographic information. The data gathered will help influence the model to better fit the community's travel patterns. The data came from the Austin Travel and America Community surveys. The tables below are labeled in three sections: Georgian Acres, Sampled, and Unsampled. Unsampled data in these figures come from the Austin Travel Survey demographic data that covers the Austin area, which includes Bastrop, Burnet, Caldwell, Hays, Travis, and Williamson Counties. The difference between the demographics of Austin and the Georgian Acres community can be seen in comparing the "Georgian Acres" and "Unsampled" columns. The Sampled column is the Austin Travel Survey sampling-based to better fit the Georgian Acres neighborhood demographics. Each category will be further explained as Income, Race, Gender, and Age.

Income

Compared to the unsampled data representing the Austin region, the Georgian Acres community has a higher percentage of people earning under $25,000 per person. Specifically, 45% of the Georgian Acres community falls into this category, while only 12% of the unsampled data does. The sampled data was able to get closer, at 34.68%. This information was an important factor in creating both the hub and the model. It's crucial to consider communities that are often overlooked in models that only reflect the travel patterns of higher-income individuals.

Table 3: Resampled percentages of trip data by income. * Georgian Acres refers to demographic information gathered from the American Community Survey

Income by Person	**Georgian Acres***	**Sampled**	**Unsampled**
Under $25,000	45.08%	34.86%	12.05%
$25,001 to $49,999	25.41%	33.24%	31.67%
$50,000 to $74,999	18.85%	16.30%	15.83%
$75,000 to $99,999	4.10%	8.57%	11.54%
$100,000 or more	6.56%	7.03%	28.91%

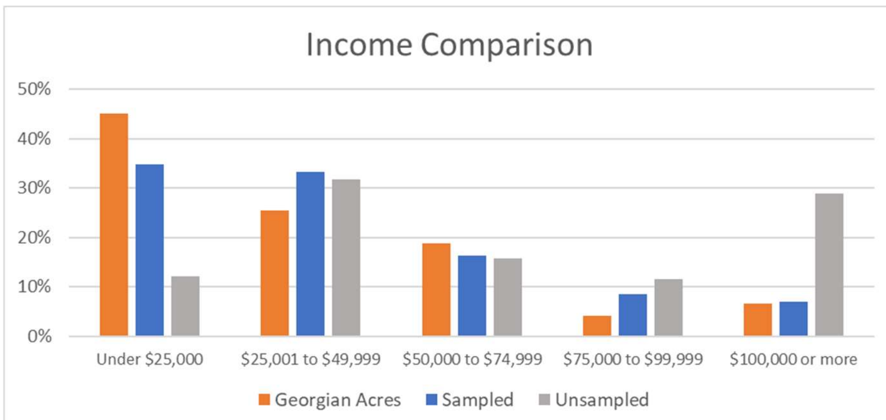


Figure 5: Resampled percentages of trip data organized into bar chart by income. * Georgian Acres refers to demographic information gathered from the American Community Survey

Therefore, it was crucial that our sample data accurately reflected the income distribution of Georgian Acres. Table 3 displays the distribution, and Figure 5 visually compares the unsampled and sampled data, highlighting how closely the orange sampled data matches the blue actual demographics. Unfortunately, we had to maximize the representation of people with incomes below $25,000 due to limitations in the unsampled data.

Race

The Georgian Acres neighborhood is a very diverse community with various races. The limitations in the number of people from each racial or ethnic background in the sampled data led to creating larger groups to ensure that we represent the large portion of non-white community members in Georgian Acres. Therefore, the categories of Non-White and White were created to maximize the responses in the survey from Non-White responses. Georgian Acres has only 25.59% of their population identifying as non-Hispanic white, which means 75.41% of the community is Non-White, which includes Hispanics. Compare this to the Unsampled Austin region, which had a majority of White responses in the Austin Travel survey at 62.52% and 37%.48 Non-White, which includes Hispanics. The sampled calculation is closer to the Georgian Acres demographics, which allows the model better to represent the racial and ethnic demographics in the model.

Table 4: Resampled percentages of trip data by race. * Georgian Acres refers to demographic information gathered from the American Community Survey

Race	Georgian Acres	Sampled	Unsampled
Non-White	75.41%	77.79%	37.48%
White	24.59%	22.21%	62.52%

Gender and Age

It is important to acknowledge that gender and age can influence the mode of transportation chosen by individuals in the Georgina Acres community. Notably, this community's male population is higher than in the Unsampled survey. However, the Sampled dataset accurately represents the neighborhood's demographics, with 54.39% male and 45.61% female. For additional details regarding this matter, please refer to Table 5.

Table 5: Resampled percentages of trip data by gender. * Georgian Acres refers to demographic information gathered from the American Community Survey

Gender	Georgian Acres	Sampled	Unsampled
Male	56.98%	54.39%	46.83%
Female	43.02%	45.61%	53.17%

The age demographics in Georgian Acres compared to the Unsampled Austin area follow similar patterns in the distribution of children and elderly. However, there are more people between the ages 18 to 34 in Georgian Acres, while there are more people in the age categories of 35 to 64 in the Unsampled data. Table 6 shows the percentages of each age group. These age groups were used as they matched the same distribution that the American Community Survey uses for age distribution.

Table 6: Resampled percentages of trip data by age. * Georgian Acres refers to demographic information gathered from the American Community Survey

Age	Georgian Acres	Sampled	Unsampled
Under 18	20.0%	22.28%	25.81%
18 to 34	34.4%	36.33%	19.85%
35 to 64	35.3%	24.46%	40.13%
65 and over	10.4%	16.94%	14.21%

In Figure 6, the age distribution of Georgian Acres is compared among three datasets: the Austin Community Survey, the Unsampled data from the Austin Travel Survey, and the Sampled data of the Austin Travel Survey. The graph shows that the Sampled data has a higher proportion of people aged '65 and over' than Georgian Acres and the Unsampled Austin region data. This is because a larger sample size of people with an income under $25,000 was needed, and people over 65 are often retired and do not have an income. Therefore, more data was collected from the Unsampled data to better reflect the income levels in Georgian Acres. The model prioritized income distribution over age distribution, but the age distribution in the Sampled dataset is still relatively accurate and an improvement on the Unsampled data.

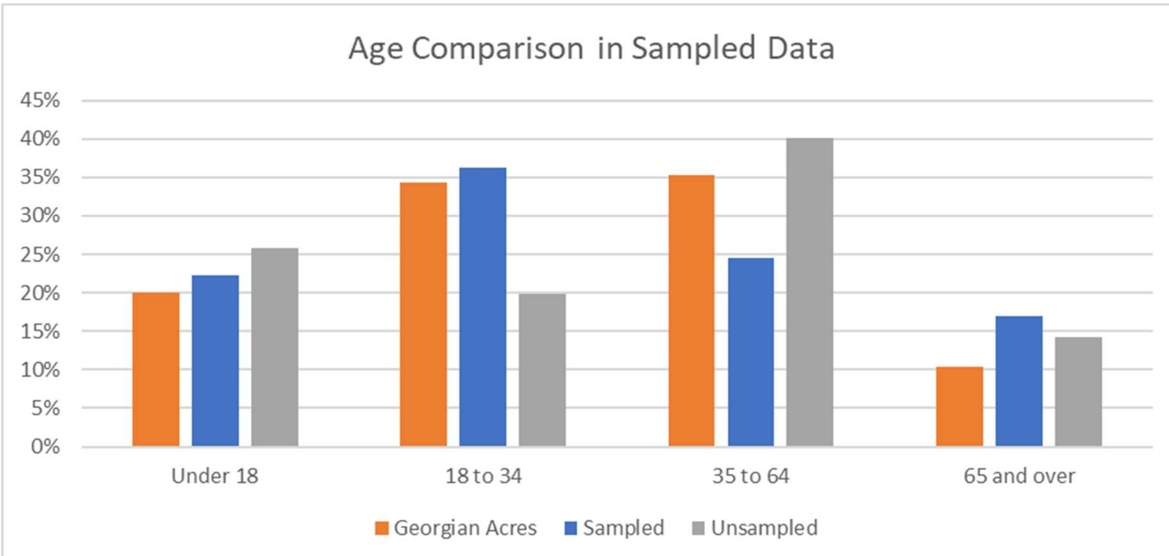


Figure 6: Resampled percentages of trip data organized into bar chart by age. * Georgian Acres refers to demographic information gathered from the American Community Survey

In order to develop a comprehensive and accurate model that accurately depicts mode choice within the Georgian Acres community, it is imperative to possess a thorough understanding of the region's demographics. Furthermore, since the objective of the hub is to promote accessibility to different modes of transportation, it is crucial to consider how individuals access these modes. As such, examining and modeling both primary and access mode choices is paramount in this particular case.

ACCESS MODES IN AUSTIN

The Georgian Acres mobility hub also hopes to contribute to the ability to supply a variety of access modes that users can take to increase access to transit. The main access modes include self-driving (park and ride), picked up or dropped off (kiss and ride), biking, and walking. However, the smart mobility hub promotes the use of e-scooters also to be included as a potential access mode that can help cover more distance than walking and be more convenient than a bike due to their ability to be parked and available anywhere. Thus, we evaluated access modes based on the Cap Metro On-Board and Austin travel surveys.

Table 6: Table of the access mode to and from the bus from CapMetro's On-Board Survey.

Mode	**To Bus Stop**	**From Bus Stop**
Drove my car	480	463
Rode a bike	422	403
Dropped off/Pick-up	506	246
Transferred from (bus/train)	2991	3563
Walked	16732	16453
All other	22	25

The Cap Metro On-Board survey conducted on buses aimed to gather information about riders, including their means of getting to the bus and their final destination. The survey sampled 21,153 riders, and Table 6 displays the results. Figure 7 illustrates the different modes of accessing the bus or train stop. The most popular access mode was walking, with 79.11% of riders walking to the bus stop. This suggests that most people walk to the bus stop because it is within walking distance. Studies by transit agencies have shown that people are generally willing to walk for 5 to 10 minutes or $\frac{1}{4}\ to\ \frac{1}{2}\ miles$ (Nabors et al., 2013). Other access modes included transferring from another bus or train

(14.1%), being dropped off or carpooling (2.4%), driving their car (2.3%), biking (2%), and other (0.1%). Most people who use the bus do so because they are within walking distance or already using another form of public transportation.

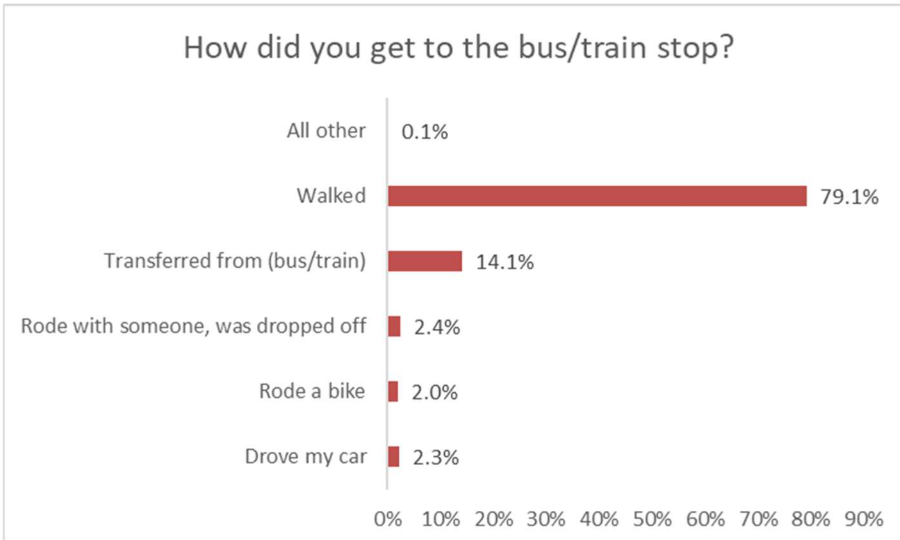


Figure 7: Access mode to bus from CapMetro's On-Board Survey.

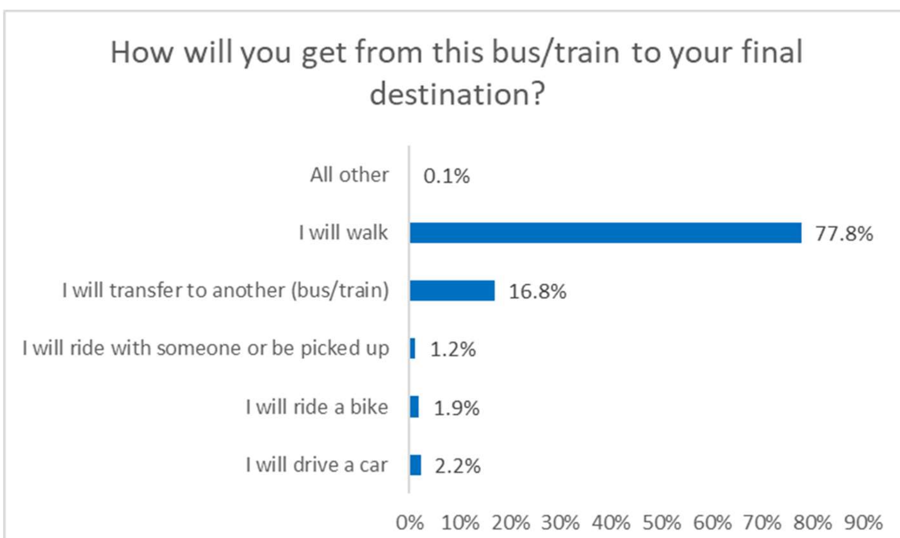


Figure 8: Access mode from the bus from CapMetro's On-Board Survey.

The chart labeled "Figure 8" presents a comprehensive overview of the various modes of transportation utilized by commuters to reach their final destination from a bus or train stop. It is observed that walking was the most preferred option, accounting for 77.8% of the total respondents. The second most common mode of transportation was transferring from another bus or train, accounting for 16.8% of respondents. Driving a personal vehicle, biking, and carpooling or picking up were less popular choices, accounting for 2.2%, 1.9%, and 1.2% of respondents, respectively.

After conducting an analysis, it has been observed that many individuals opt to walk to transit stops to access public transportation or reach their destination. This suggests that most people are willing to travel short distances on foot to avail themselves of transit services. It is plausible that this is due to the unavailability of other transportation options that cater to longer distances beyond the $\frac{1}{4}\ to\ \frac{1}{2}\ miles$ mile range. Such transportation modes include bus or train transfers, cycling, and driving oneself. However, it should be noted that the survey data was collected in 2015, before the rise of e-scooters and the expansion of e-bike docking stations in 2017 and 2018 (Jiao et.al., 2020; Cobler, 2023). Consequently, there may have been an increase in the usage of shared scooters and bikes by transit users. The Austin Travel Survey, which was conducted from 2016-2018, could provide valuable insights into this trend.

The Austin Travel Survey was assessed to determine the means of transportation used to access transit in the city. There are two methods to analyze access modes since they do not directly inquire about a person's mode of transportation. Method One examines the trip taken before and after a bus journey to determine which modes were used to reach and depart from the bus stop. This method focused on identifying the access mode to the bus. Separating bus and school buses was necessary as the results varied significantly between the two modes. The total number of sample trips obtained through this method was 285.

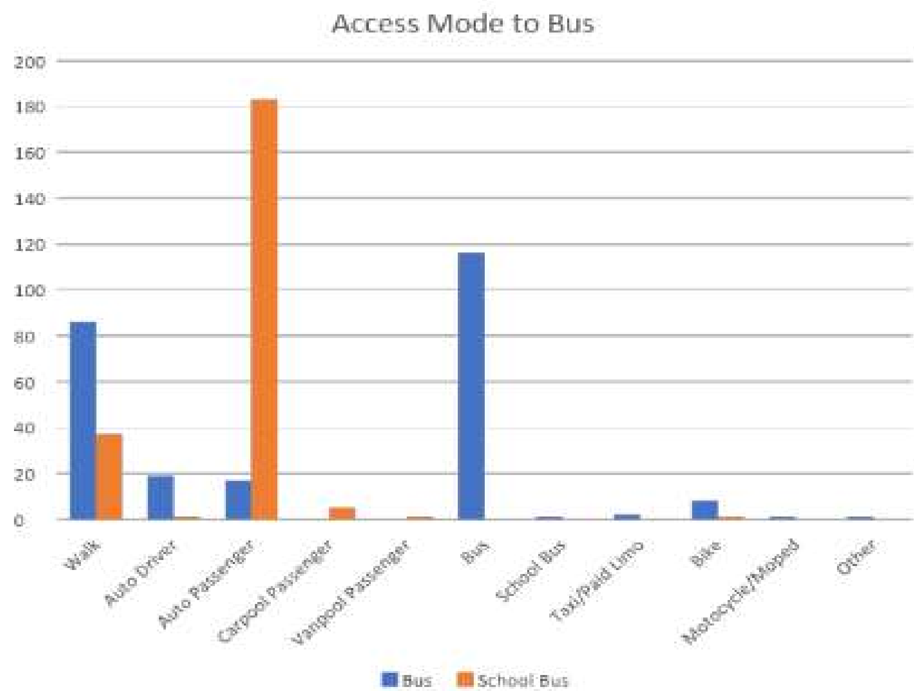


Figure 9: Access mode to the bus using data from Austin Travel Survey.

To gather additional trip samples for access mode analysis, we explored alternative methods of categorizing access. Method Two uses trip purpose to assess access modes, with Pick-Up, Drop-Off, and Change Mode as the selected purposes. As a result, we obtained 604 sample trips, bringing the total number of access mode trips between Method One and Two to 807. For a visual representation of this methodology, refer to Figure 11.

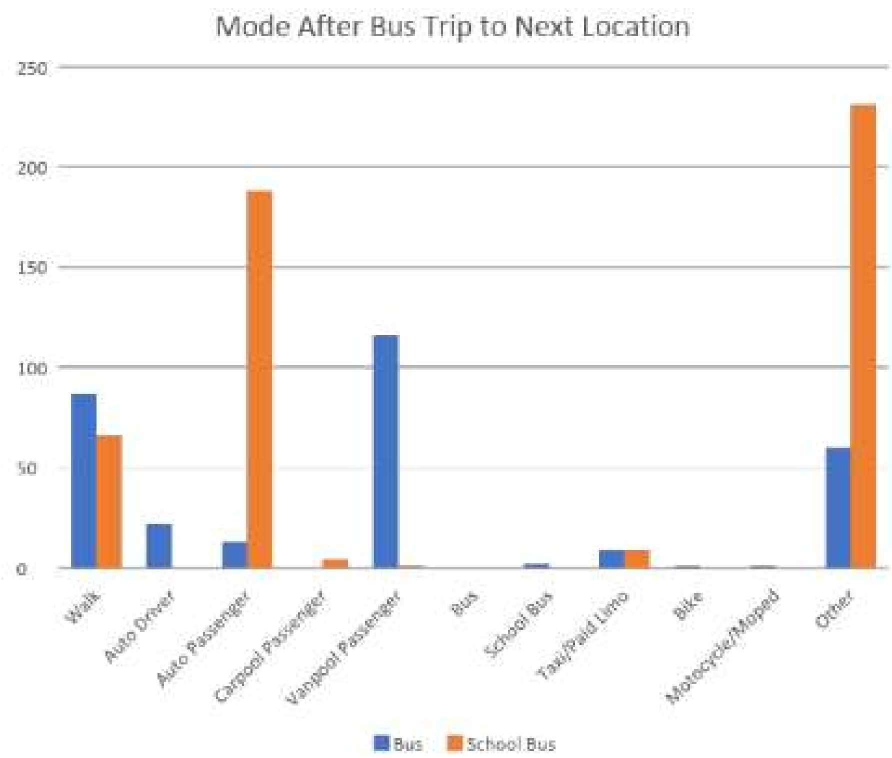


Figure 10: Access mode to the bus using data from Austin Travel Survey.

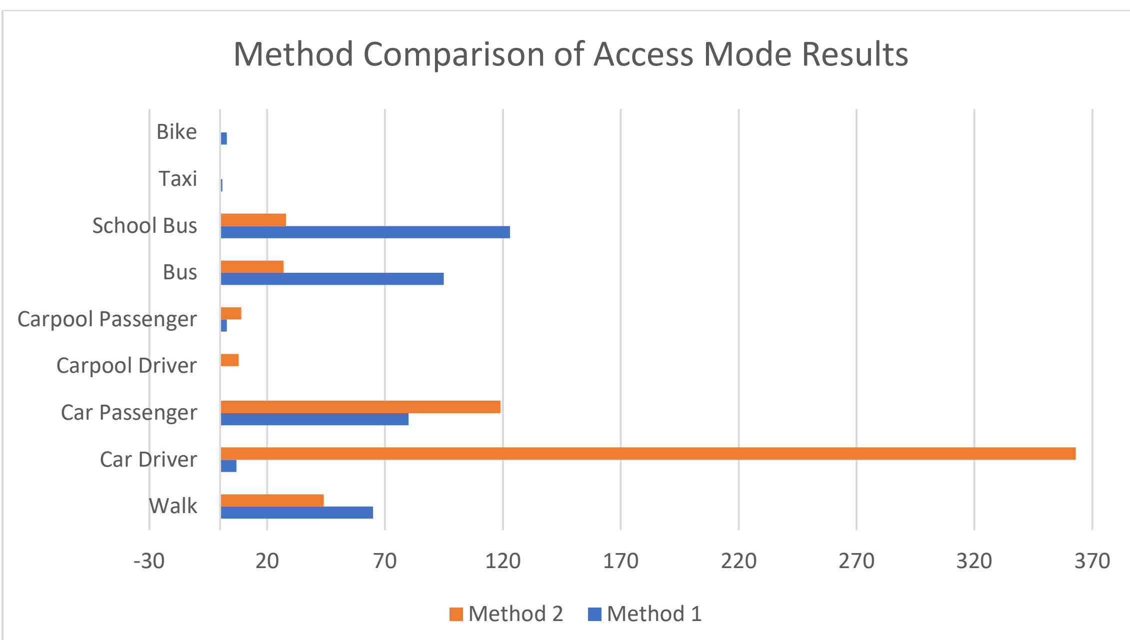


Figure 11: Comparison of Method 1 and Method 2 of Getting Access Mode from the Austin Travel Survey.

To effectively analyze the impact of both methods, we will integrate them and proceed with necessary adjustments. However, we must first establish a base model to comprehensively understand the current transit demand and population behaviors under study.

POST-HUB SURVEY

The Post-Hub survey was conducted while the hub was working to get feedback directly from the community. The gender, racial, and income demographics are closely related to the overall demographic representation of Georgian Acres.

Tables 7 and 8: Race and Income demographics of those who took the post-hub survey.

Race	Percentage
Asian	4%
Black and/or African American	12%
Hispanic or Latinx	33%
Native Hawaiian or Other Pacific Islander	3%
Native/Indigenous	5%
White	43%

Income	Percentage
Under $20,000	20%
$20,001 to $40,000	20%
$40,001 to $60,000	15%
$60,001 to $80,000	23%
$80,001 to $100,000	16%
$100,000 or over	5%

The travel characteristics of individuals utilizing the Georgian Acres hub have been analyzed and presented in Tables 9 and 10. The data reveals that households with an average of four members and those lacking access to personal vehicles were the most frequent users of the hub. This suggests that such households rely heavily on services like the mobility hub.

Table 9: From the Post Hub Survey, the questions asks the number of people in the household.

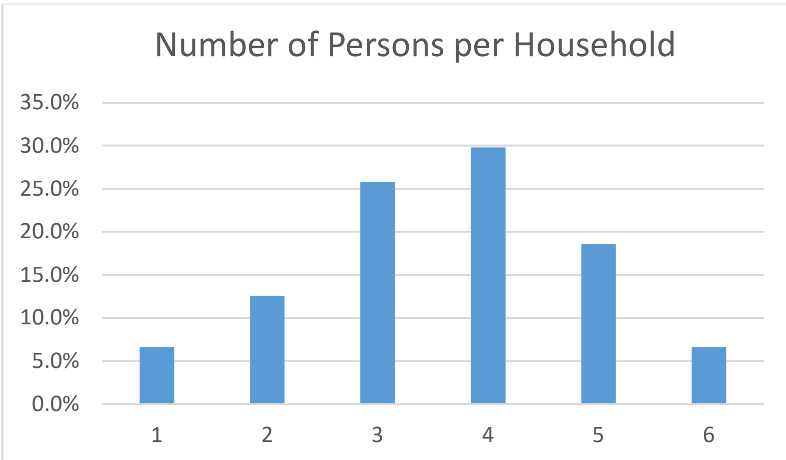
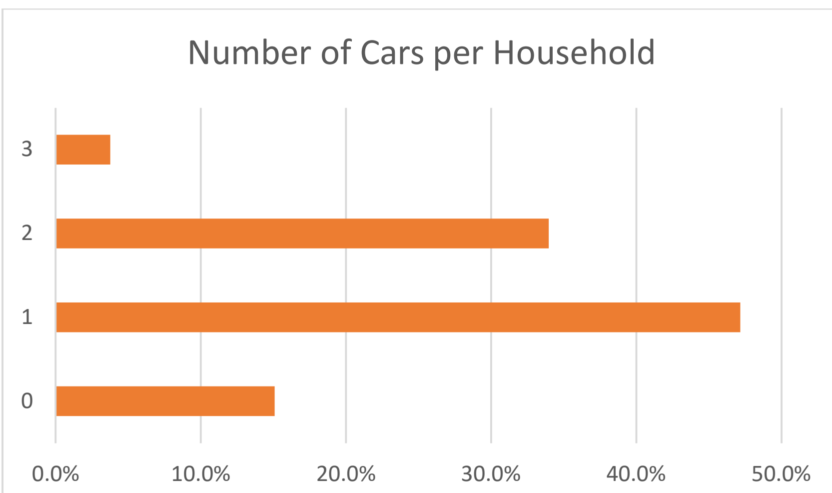


Table 10: From the Post Hub Survey, the questions ask the number of cars per household.



Chapter 4: Modeling Access Mode Choice for the Georgian Acres Community

DATA

The data from the 2017 Austin Travel Survey and the Capital Area Metropolitan Planning Organization (CAMPO) Model was utilized to construct the underlying multinomial logit model. The CAMPO model provided us with Traffic Analysis Zones for the Austin region, Austin Network, and Transit skim tables, which included the cost of traveling by transit. To prepare the data, we first used resampled trips from the Austin Travel survey to match the demographics of Georgian Acres.

Resampling the 2017 Austin Travel Survey

The Austin Travel Survey data had to be resampled to be helpful in modeling the mode choice behaviors of the Georgian Acres neighborhood. Table 7 shows the weights of each gender to balance the demographics. Table 8 shows the weights placed on the different age groups. Table 9 shows the weights on a combination of race and income on the Austin Travel Survey to balance it for the Georgian Acres demographics.

Table 9: Percentages of trip data by gender comparison and weights to be applied. * Georgian Acres refers to demographic information gathered from the American Community Survey

Gender	Georgian Acres Demographics *	Austin Travel Survey Demographics	Weight Gender
Male	56.98%	44.96%	1.26738178
Female	43.02%	55.04%	0.78156205

Table 8: Percentages of trip data by age comparison and weights to be applied.

* Georgian Acres refers to demographic information gathered from the American Community Survey

Age	Georgian Acres Demographics *	Austin Travel Survey Demographics	Weight Age
Under 18	20.0%	22.56%	0.88443497
18 to 34	34.4%	19.76%	1.73861189
35 to 64	35.3%	44.48%	0.7936833
65 and over	10.4%	13.20%	0.78697070

Table 10: Percentages of trip data by race and income comparison and weights to be applied. * Georgian Acres refers to demographic information gathered from the American Community Survey

Income and Race		
Georgian Acres Demographics *	**Non-White**	**White**
Under $25,000	39%	6%
$25,001 to $49,999	19%	7%
$50,000 to $74,999	13%	6%
$75,000 to $99,999	2%	2%
$100,000 or more	2%	5%
Austin Travel Survey Demographics	**Non-White**	**White**
Under $25,000	7%	6%
$25,001 to $49,999	11%	12%
$50,000 to $74,999	6%	13%
$75,000 to $99,999	4%	8%
$100,000 or more	7%	26%
Weighted	**Non-White**	**White**
Under $25,000	5.95	0.93
$25,001 to $49,999	1.69	0.56
$50,000 to $74,999	2.11	0.43
$75,000 to $99,999	0.67	0.19
$100,000 or more	0.24	0.19

METHODOLOGY

In transportation planning, the base model typically involves a four-step approach that includes demand modeling and forecasting. The four-step model consists of trip generation, trip distribution, mode choice, and trip assignment, as McNally (2008) outlined and shown in Figure 11. This framework is then utilized for different scenarios using modeling methods discussed in the literature review.

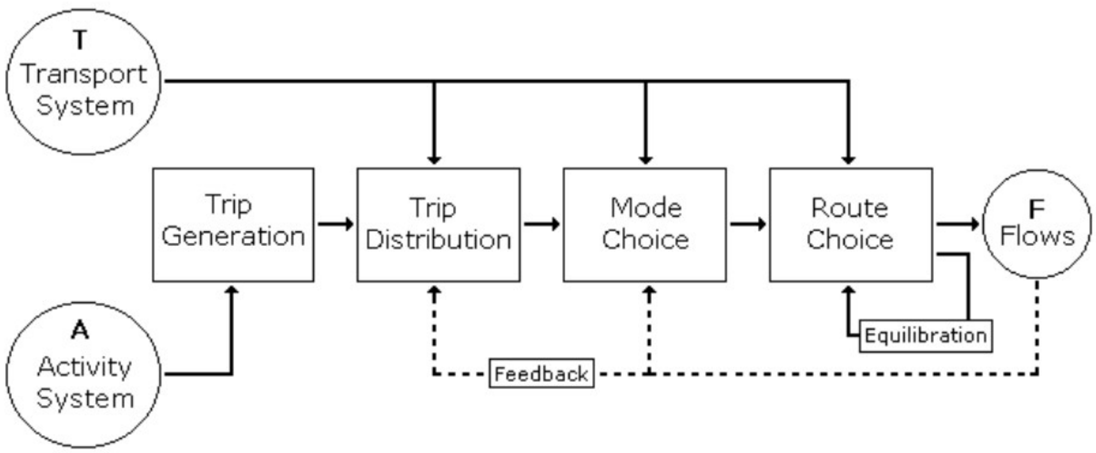


Figure 12: Four-Step Model Visualization (McNally, 2008)

Trip Generation

During this phase, we aim to determine the number of journeys originating from or ending in a particular zone or area, referred to as Traffic Assignment Zones (TAZ). These journeys are classified as Trip Productions if they commence within the TAZ and Trip Attractions if they culminate in the same. To derive the number of trips generated and attracted to a specific region, we assess various factors such as population, employment rate, land usage, and socioeconomic characteristics of the area. For instance, a zone in the Central Business District (CBD) has a high concentration of businesses but a low density of residential properties. Additionally, we classify these journeys based on their category.

- Home-Based Work (HBW): These trips are often a large percentage of trips made in modeling travel demand. HBW trips are commutes from home to work and back to home. These do not include any trips for errands between home and work commuting.
- Home-Based Other (HBO): Trips that begin or end at home unrelated to work. These trips often include shopping and recreational activities.
- Non-Home Based (NHB): These trips do not begin or end at home or work location. These trips are typically not a part of someone's regular commute but include business travel, commuting to school or other educational institutions, or between two destinations, such as shopping and doing a recreational activity.

Trip Production

The model for trip production estimates the number of trips originating from a specific geographic area. In this case, we are utilizing TAZs in the Austin region, which contain data on population, employment, and other relevant demographic and socioeconomic factors that can impact trip production within each TAZ (McNally, 2008). Trip rates must be developed based on the TAZ's demographic data to calculate the number of trips in these zones. These rates show the average number of trips per person, per trip purpose, or per household. This study's trip rates are derived from the NHCRP Rates for trip production. These rates are based on the urban size of Austin and the number of persons per household.

Table 10 predicts the total number of trips produced based on the urban size. These numbers are further used by predicting the number of trips by purpose and how many originate in each TAZ zone by relating the frequency of trips to the characteristics of the household or individual.

Table: 10: Trip Estimation Variables by Urban Size

Urbanized Area Size = 50,000 - 199,999 (Persons per HH)

	1	2	3	4	5+	Average
Low	3.6	6.5	9.1	11.5	13.8	6
Medium	3.9	7.3	10	13.1	15.9	9.3
High	4.5	9.2	12.2	14.8	18.2	12.7
Average	3.7	7.6	10.6	13.6	16.6	9.2

Cross classification Method

The cross-classification method was used in the travel demand modeling to analyze and understand the characteristics and behavior of the Georgian Acres community based on their demographic and trip-specific attributes. The population was categorized by persons into different groups based on attributes such as gender, income level, and race. The goal is to create meaningful categories that capture the diversity of the Georgian Acres population. The dependent variables, such as income, age, and race, are cross-tabulated with the travel variables, such as mode choice, trip purpose, and trip distance. This analysis helps identify patterns or differences in travel behavior across different groups in the Georgian Acres community. This will help the model better predict the travel behavior of different demographics based on variations in mode choices, trip purposes, travel distances, or other factors. These insights can inform the development of targeted strategies to meet the diverse needs of different traveler groups using the community hub.

Trip Attraction

Trip attraction estimates the number of trips attracted to each zone or destination within each TAZ in Austin based on the trip distribution results. This is typically done by summing up the trips assigned to each zone as the destination in the trip distribution matrix. The estimated trip attraction values provide insights into the attractiveness or desirability of different zones as destinations. It helps understand the flow of trips, identify major activity centers or destinations in Austin, and assess the impact of land-use patterns, transportation infrastructure, and other factors on trip generation and distribution. By estimating the number of trips attracted to each zone, the trip attraction step contributes to understanding travel patterns, demand for transportation services, and planning for transportation infrastructure and services for the Georgian Acres community, which can be applied to other communities.

Trip Balancing

Trip balancing is performed after creating the trip productions and attractions to adjust the trip distribution matrix to align the estimated trip volumes with the known or desired total trip volumes. This adjustment redistributes the trip volumes within the matrix while maintaining the overall row and column totals to keep the trips produced and attracted the same. The trip balancing process is often iterative, requiring multiple iterations to achieve convergence between the estimated and desired trip volumes. The adjustment factors in the balancing process are typically derived from the observed trip volumes in the Austin Travel Survey based on different trip purposes. These are applied to the initial trip distribution matrix until the desired convergence is achieved to help ensure that the travel demand model accurately represents the observed travel patterns in Georgian Acres.

Trip Distribution

Trip distribution takes the origins and destinations of the trips estimated after trip balancing and assigns them to specific locations within the Austin area. The distribution of trips helps to understand the spatial patterns of travel demand. It also helps determine the number of trips traveling between each OD pair by TAZ. It involves considering factors such as distance, travel times, transportation modes, land use patterns, and other variables influencing travel behavior. The trip distribution model is calibrated and validated using observed travel data from the Austin Travel Survey. This helps ensure that the estimated trip distribution accurately represents Austin's travel patterns based on travel factors. The output of the trip distribution step is a trip distribution matrix, which specifies the estimated number of trips traveling between each OD pair by TAZ. The trip distribution matrix allows us to understand the flow of trips across the transportation network, identify main travel corridors, and evaluate the impact of the mobility hub infrastructure on the communities in Austin.

Gravity Model

The gravity model was used for the trip distribution step to estimate the number of trips traveling between different origin-destination (OD) pairs within a study area. The gravity model assumes that the number of trips between two zones is proportional to the product of their population or employment sizes and inversely proportional to the distance between them (Apronti, 2016). For the gravity function in our model, we based it on travel times, transportation costs, and other impedance factors. By comparing the observed trip volumes from the Austin Travel Survey with the estimated trip volumes based on the gravity model, the model's parameters can be adjusted to improve the accuracy of the estimated trip distribution. The gravity model provides a simplified representation of the relationship between trip generation and trip distribution by creating a framework for estimating trip volumes based on the attractiveness of destinations and the travel impedance between origins and destinations.

Mode Choice

Once the trip distribution is determined, individuals or households decide which transportation mode to use for their trips. The mode choice step involves analyzing the modes available to travelers and predicting which modes they will likely choose based on travel time, cost, convenience, reliability, and personal preferences. The mode choice models estimate the probability or likelihood of selecting either car or bus mode based on these factors and the characteristics of the traveler and the trip. The model is based on a discrete choice model - nested logit models, which allow for the analysis of the trade-offs and preferences of individuals when choosing between different transportation modes into a modal split. The output is a mode choice model that provides insights into the distribution of trips across different transportation modes, such as how likely a gender, gender, or other factors are to choose between bus and car. The modal split applies the mode choice model to allocate the trips to different transportation modes. The proportion or percentage of trips assigned to each mode is calculated based on the mode choice model results. For example, the mode choice model can decide between car and public transit. Thus, the modal split might indicate that 70% of the trips are assigned to cars, 30% to buses. This information can become an iterative process as we understand the modal split of the demographics under the model and then serves as input for the subsequent step in the modeling process.

Trip Assignment

The final step involves assigning the predicted trips to the transportation network, including roads, public transit, and other modes. This step helps to estimate the traffic volumes on different routes and modes and to identify potential bottlenecks and congestion hotspots to determine which routes or paths travelers will take based on their chosen modes of transportation. In this model, travelers can choose between a bus or a car. In trip assignment, the transportation network is represented by a network of nodes and links, where nodes represent the origins and destinations based on the travel behavior in the Austin Transit Survey. The links in the network represent the physical infrastructure, such as roads, highways, or transit lines connecting the nodes. The goal is to determine the flow of trips on each network link.

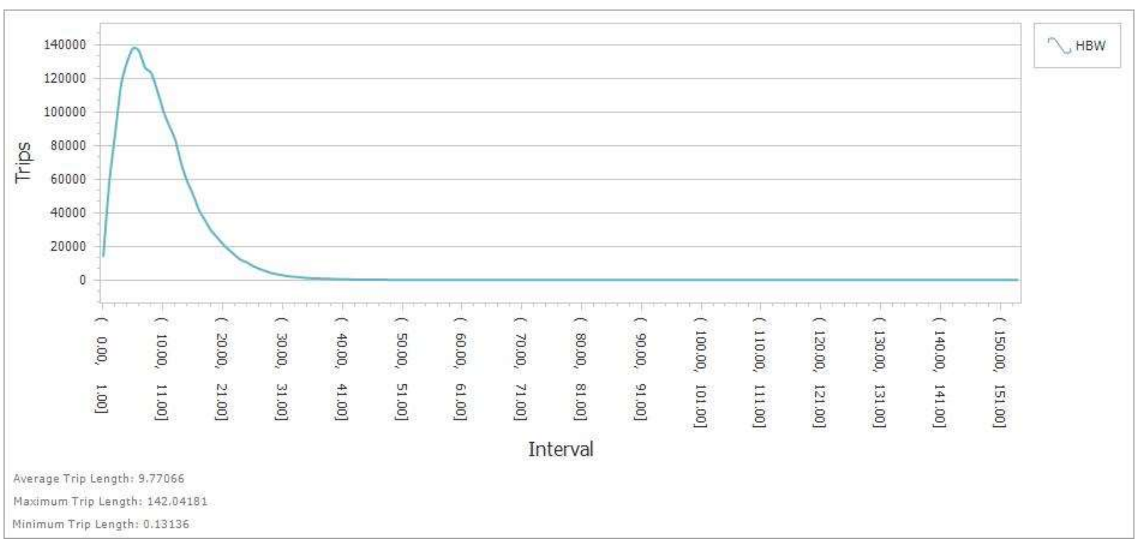
Static traffic assignment will be used for the model, in which the trips are assigned to the network based on predetermined travel costs or attributes of the links, where travel demand is allocated to the transportation network based on fixed conditions without considering the interactions and feedback loops between travelers and the network, which would require a dynamic travel assignment. The model will allocate trips onto the network based on the shortest path and lowest travel cost, assuming that travelers choose the most efficient routes available to them without considering the impact of their choices on overall network conditions.

Chapter 5: Findings

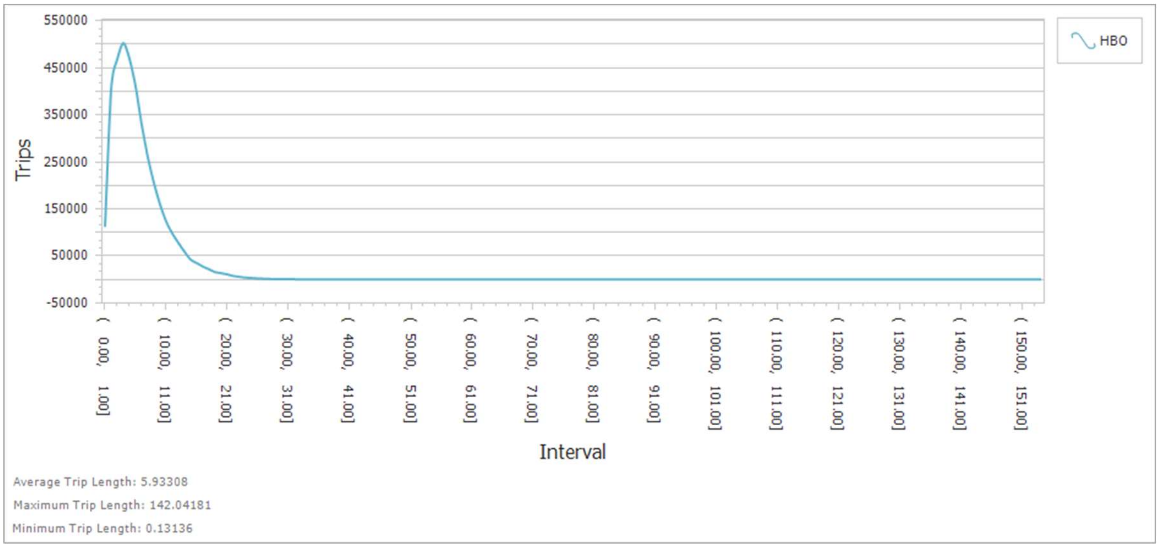
FIRST MODEL

From the resampling of the Austin Travel Survey, the model will contain 6,332 trips out of the 35,699 that were initially in the Austin population to reflect the demographics of the Georgian Acres community. After the trips were generated based on the Austin Travel Survey, the trips had to be distributed based on the Austin TAZs. From this, we can use the gravity model to understand the relationship between number of trips and trip length by purpose. These Trip Length Distribution graphs are shown in Figure 13 as Home-Based Work trips, Home-Based Other trips, and Non-Home-Based trips.

HBW



HBO



NHB

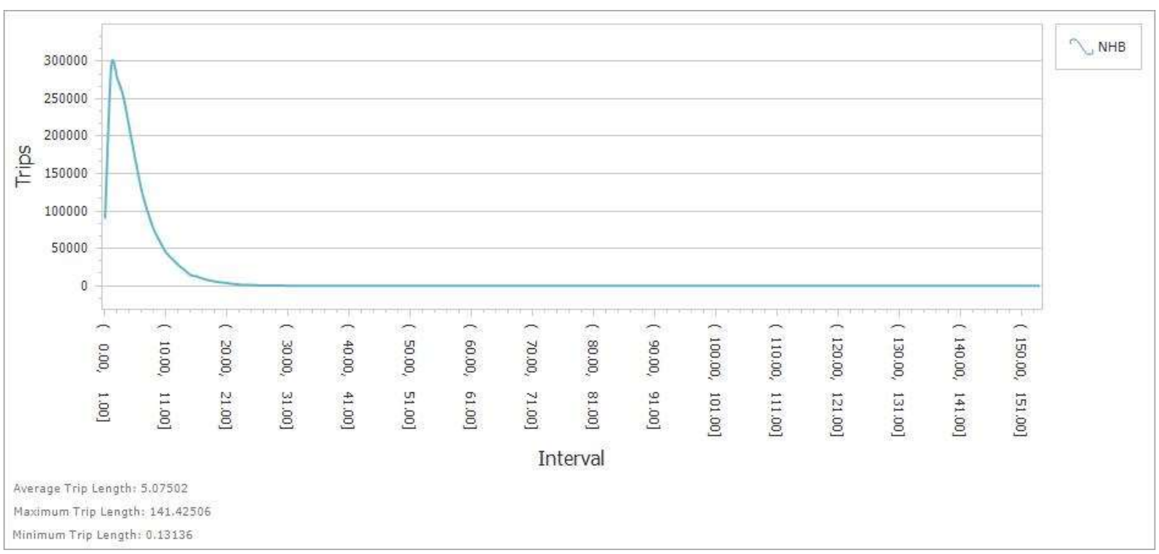


Figure 13: Trip Length Distribution graphs using the Gravity Application of the Models Trip Distribution (HBW, HBO, NHB).

The distribution of trip length, as presented in Figure 13, reveals a decrease in the number of trips as the distance and cost of the trip increase. This pattern is consistent with the intended purpose of each trip. Notably, the average length of home-to-work (HBW) trips is the longest, suggesting a greater willingness of individuals to travel long distances for work-related trips. In general, commuting to work from home involves longer distances compared to other types of trips.

Table 11 Resampled Survey - Summary Statistics of Mode Choice by Purposes

Purpose	**Count**	**Percentage of Total**
HBNW	3218	**50.8%**
HBW	16	**0.25%**
NHBO	2507	**39.59%**
NHBW	591	**9.33%**

Next, a summary statistic of our sample in the model based on purpose can give information about their mode choice. Table 11 shows the distribution of trips in the sample in the model based on purpose. Comparing the percentages of each trip purpose to that of the original Austin Travel Survey trip distributions shown in Table 12, there is an apparent discrepancy between the percentages. It seems as if our sample is not displaying the HBW trips as accurately. However, it is good to note that most trips are made as Home-Based Non-Work and Non-Home-Based Other trips. This information is also reflected in the Trip

Length Distribution graphs shown in Figure 13. Therefore, this was the first issue the model posed to its ability to represent the population. However, the mode choice model was processed using these samples to be further evaluated.

Table 12 Original Austin Travel Survey - Summary Statistics of Mode Choice by Purposes

Purpose	**Count**	**Percentage of Total**
HBNW	16208	**45.9%**
HBW	4096	**11.6%**
NHBO	12660	**35.87%**
NHBW	2335	**6.6%**

Mode Choice

In the given mode choice model test results, the coefficients and t-test scores are provided for several independent variables compared to the reference category of "Driving a Car," the alternative mode is "Taking Public Transit." The results for the following independent variable are shown in Table 12, which shows the coefficient and the test for each variable. In a mode choice model, the coefficient represents the estimated effect or impact of an independent variable on the choice of a particular mode of transportation by quantifying the relationship between the independent variable and the likelihood of selecting a specific mode, such as a bus, relative to driving a car. Independent variables such as travel time, travel cost, income, and other factors are included to explain the variation in mode choice by estimating the coefficients associated with these independent variables. The t-test evaluates whether the estimated coefficients differ significantly from zero, indicating whether the independent variables significantly impact the choice of transportation modes. The null hypothesis assumes that the coefficient equals zero, implying that the independent variable does not affect mode choice. The alternative hypothesis assumes that the coefficient is not equal to zero, suggesting that the independent variable significantly impacts mode choice. A higher t-test score indicates more robust evidence against the null hypothesis and suggests a more significant impact of the independent variable on mode choice. The analysis for each of these variables is as follows:

- Time: The coefficient for the "Time" variable suggests that, compared to driving a car, a one-unit increase in travel time is associated with a decrease of 0.00155 in the likelihood of choosing the bus as the mode of transportation. This makes sense since an increased travel time means that taking a bus is less likely. However, the t-test score of -0.3185 indicates that this effect is not statistically significant at the conventional significance level.
- Income: The coefficient for the "Income" variable indicates that, compared to driving a car and holding other variables constant, a one-unit increase in income is associated with a decrease of 0.00846 in the likelihood of choosing the bus. As people have higher incomes, they are less likely to take the bus. However, like the "Time" variable, the t-test score of -0.3215 suggests that this effect is not statistically significant.

- Vehicles Per Household: The coefficient for the "Vehicle Per Household" variable suggests that, compared to driving a car, having one additional vehicle per household is associated with a decrease of 2.81798 in the likelihood of choosing the bus as the mode of transportation. This makes sense since a household with many cars is more likely to use them than take the bus. Notably, the t-test score of -10.0383 indicates that this effect is statistically significant at a high significance level.
- Gender: The coefficient for the "Female" variable indicates that, compared to driving a car, being female is associated with an increase of 1.10531 in the likelihood of choosing the bus as the mode of transportation. This variable is the most irregular result, as women often take cars according to other studies that examine mode choice due to parental duties (Guiver, 2007). The t-test score of 3.2612 suggests that this effect is statistically significant.

Table 13: Mode Choice Model Results of Resampled Model

Field	**Coefficient**	**t-test**
Time	-0.001547883691844	-0.3185
Income	-0.008464481419947	-0.3215
Vehicle Per Household	-2.817982907476836	-10.0383
Female	1.105314294369897	3.2612

Some issues with the summary statistics and mode choice modeling led to several insignificant and irregular outcomes. A thorough re-evaluation of the model was conducted to guarantee that the sample population was accurately represented. This included carefully examining the calculations for trip time, length, trip purpose, and cost and then re-running the model.

MODEL VERSION 2 (V2)

After recalculating the purpose of trips for the model, the summary statistics were re-evaluated to determine the distribution of trips by purpose. The results of the second sample run of the model are shown in Table 14. The percentages of the new results are more closely aligned with the original Austin Travel Survey results in Table 12, compared to the previous model in Table 11.

Table 13 Model V2 Resampled Survey - Summary Statistics of Mode Choice by Purposes

Purpose	**Count**	**Percentage of Total**
HBNW	2896	**45.7%**
HBW	711	**11.2%**
NHBO	2343	**37%**
NHBW	382	**6.03%**

Mode Choice Model Results

- Age: The coefficient for the "Age" variable suggests that, compared to driving a car, a one-unit increase in age is associated with a 0.04034 increase in the likelihood of choosing the bus as the mode of transportation. The t-test score of 6.0376 indicates that this effect is statistically significant at the conventional significance level. Therefore, age appears to have a significant positive impact on choosing the bus as the mode of transportation.
- Income: The coefficient for the "Income" variable indicates that, compared to driving a car, a one-unit increase in income is associated with a 0.04297 increase in the likelihood of choosing the bus. The t-test score of 2.0770 suggests this effect is statistically significant and more significant than the first model run.
- Vehicles Per Household: The "Vehicle Per Household" coefficient suggests that, compared to driving a car, having one additional vehicle per household is associated with a 2.852477 increase in the likelihood of choosing the bus as the mode of transportation. The t-test score of 5.6706 indicates that this effect is statistically significant. This variable changed a lot from the previous model, which made more sense in that households with more cars will drive more than those who do not.

Table 14 Mode Choice Model Results of Resampled Model V2

Field	**Coefficient**	**t-test**
Age	0.040341696043697	6.0376
Income	0.042973800505693	2.0770
Vehicle Per Household	2.852477484207555	5.6706
Female	0.027496	0.0742

MODEL FINAL VERSION (V3)

In the final version of the mode choice model, the resampled modal distributions from Table 16 were utilized to represent the mode choices of the survey respondents. The graph presents the mode distributions for different transportation options and the counts of valid observations for each mode category. Among the valid observations, the majority of respondents (87.8%) opted for Mode 1, representing either "Drive alone" or "Carpool" as their primary mode of transportation. A smaller percentage (6.9%) preferred Mode 2, indicating that "Walk" or "Bike" served as their primary mode. For public transit options, Mode 31, which corresponds to "Bus with walking access," accounted for 1.7% of respondents, while Mode 32, representing "Bus with non-walking access," constituted 3.6% of the valid observations. These resampled modal distributions provide valuable data inputs for the mode choice model, enabling a comprehensive analysis of the factors influencing commuters' mode preferences that would influence the model.

Table 15 The Sample Modal Distributions for The Datasets Used For Choice Modeling

	All Austin Survey		Resampled Survey	
Mode	**Count**	Percentage	**Count**	Percentage
No data	55		31	
1 (Drive alone or carpool)	24918	89.9%	4252	87.8%
2 (Walk/Bike as main mode)	1694	6.1%	333	6.9%
31 (Bus walking access)	306	1.1%	82	1.7%
32 (Bus non-walking access)	811	2.9%	176	3.6%
Total (with valid observations)	27729	100%	4843	100%

The model will analyze the factors influencing commuters' mode preferences based on various independent variables. The dependent variables, represented by the modes, include: "Cost," representing the cost associated with each mode; "Time," representing the travel time for each mode; "OTime2Bus," referring to the origin's time to access the bus stop; "DTime2Bus," indicating the destination's time to access the bus stop; "VehpcDR," representing the number of vehicles per household for those who drive alone; "HHSizeDR," indicating the household size for those who drive alone; "FemaleBus," representing the female respondents who opt for the bus mode; "FemaleWalkAcc," indicating the female respondents who prefer walking with bus access; "Age2035," representing respondents aged between 20 to 35 years; and "Age3550," indicating respondents aged between 35 to 50 years. The independent variables include "Const(Drive)," "Const(BUS)," and "Const(WalkAcc)," which serve as constants for the respective modes. The results of this model are shown in Table 16.

Table 16 Mode Choice Model Results of Resampled Model V3

Field	**Coefficient**	**t-test**
Cost	-0.2127277	0.058159
Time	-0.06852061	0.004693
OTime2Bus	-0.00407135	0.001229
DTime2Bus	0.00103071	0.000312
VehpcDR	3.465187046	0.199792
HHSizeDR	0.07401428	0.032865
FemaleBus	0.50687627	0.160243
FemaleWalkAcc	-0.24909324	0.279886
Age2035	-0.68622563	0.176827
Age3550	-0.919832614	0.245168
Const(Drive)	-1.24286617	0.190202
Const(BUS)	-2.21632264	0.157415
Const(WalkAcc)	-0.07765391	0.225393
Log-Likelihood at Zero	-6713.82	
Log-Likelihood at Start	-1811.18	
Log-Likelihood at End	-1757.84	
-2 (LL(Zero) - LL(End))	9911.967	
-2 (LL(Start) - LL(End))	106.677	
Asymptotic rho squared	0.7382	
Adjusted rho squared	0.7362	

Mode Choice Model Results

The results of the final mode choice model test explain how the travel patterns of the Georgian Acres community can be modeled. Table 16 displays the Austin Travel Survey that was sampled to represent the Georgian Acres community and is also compared to the overall Austin Travel Survey in Table 17. The results for each variable in Table 16 are explained below:

- Cost: The coefficient of -0.2127 indicates that an increase in the cost variable is associated with a decrease in the likelihood of choosing a specific mode. However, the t-test statistic 0.0582 suggests that the relationship between cost and mode choice is not statistically significant.
- Time: The coefficient of -0.0685 implies that an increase in travel time is associated with a decrease in the likelihood of selecting a particular mode. The t-test statistic of 0.0047 suggests that this relationship is statistically significant, indicating that travel time is a significant factor in mode choice decisions.
- OTime2Bus: The coefficient of -0.0041 indicates that an increase in the origin's time to access the bus stop is associated with a slight decrease in the likelihood of choosing the bus mode. The t-test statistic of 0.0012 suggests that this relationship is statistically significant.
- DTime2Bus: The coefficient of 0.0010 suggests that an increase in the destination's time to access the bus stop is associated with a slight increase in the likelihood of

choosing the bus mode. The t-test statistic of 0.0003 indicates that this relationship is statistically significant.

- VehpcDR: The coefficient of 3.4652 indicates that an increase in the number of vehicles per household for those who drive alone is associated with a significant increase in the likelihood of choosing the driving mode. The t-test statistic of 0.1998 suggests that this relationship is statistically significant.
- HHSizeDR: The coefficient of 0.0740 suggests that an increase in household size for those who drive alone is associated with a slight increase in the likelihood of choosing the driving mode. The t-test statistic of 0.0329 indicates that this relationship is statistically significant.
- FemaleBus: The coefficient of 0.5069 suggests that female respondents are more likely to choose the bus mode than other modes. However, the t-test statistic of 0.1602 indicates that this relationship is not statistically significant.
- FemaleWalkAcc: The coefficient of -0.2491 suggests that female respondents with bus access through walking have a slightly lower likelihood of choosing this mode. However, the t-test statistic of 0.2799 indicates that this relationship is not statistically significant.
- Age2035: The coefficient of -0.6862 suggests that respondents aged between 20 to 35 years have a lower likelihood of choosing a particular mode. However, the t-test statistic of 0.1768 indicates that this relationship is not statistically significant.

- Age3550: The coefficient of -0.9198 suggests that respondents aged between 35 to 50 years have a lower likelihood of choosing a particular mode. However, the t-test statistic of 0.2452 indicates that this relationship is not statistically significant.

Overall, the mode choice model test results provide insights into the relative importance of the time, the origin's and destination's time to access the bus stop, the number of vehicles per household for those who drive alone, and household size variables in influencing mode choices for the Georgian Acres community. Table 17 shows the mode choice model results for the unsampled Austin Travel Survey.

Table 17 Mode Choice Model Results of Unsampled Model (Entire Austin Travel Survey)

Field	**Coefficient**	**t-test**
Cost	-0.39688531	-12.6568
Time	-0.07189807	-12.6568
OTime2Bus	-0.00101449	-3.1655
DTime2Bus	0.00004314	1.3660
VehpcDR	2.11485098	24.6280
HHSizeDR	0.06701517	3.8454
FemaleBus	0.51051743	6.9719
FemaleWalkAcc	-0.73170005	-5.2865
Age2035	-0.22637201	-2.9545
Age3550	-0.77701166	-9.8879
Const(Drive)	-0.73931871	-7.1572
Const(BUS)	-2.079110105138941	-31.6708
Const(WalkAcc)	-0.427184067129298	-4.3369
Log-Likelihood at Zero	-38304.70	
Log-Likelihood at Start	-9228.93	
Log-Likelihood at End	-9228.55	
-2 (LL(Zero) - LL(End))	58152.302	
-2 (LL(Start) - LL(End))	0.757	
Asymptotic rho squared	0.7591	
Adjusted rho squared	0.7587	

Comparing the sampled model in Table 16 to the results of the unsampled model in Table 17, we can observe some similarities and differences in the model's findings. In both tables, the Cost and Time variables consistently have negative coefficients, suggesting that higher costs and longer travel times are associated with a reduced likelihood of choosing a specific mode. Similarly, VehpcDR and HHSizeDR variables have positive coefficients in both tables, indicating that an increase in the number of vehicles per household for those who drive alone and a larger household size for those who drive alone corresponds to a higher likelihood of choosing the driving mode. These relationships are statistically significant in both samples, indicating the importance of cost and time considerations and the role of household characteristics in influencing mode choice decisions for the Georgian Acres community and the Austin region.

However, some differences exist between the two tables. For instance, the "FemaleBus" variable has a positive coefficient in Table 16, suggesting that female respondents are more likely to choose the bus mode in Georgian Acres. In contrast, Table 17 shows a similar positive coefficient but with a higher t-test statistic, indicating a stronger statistical significance for this relationship. The "FemaleWalkAcc" variable also shows different results in the two tables. Table 16 has a negative coefficient, suggesting that female respondents with bus access through walking have a slightly lower likelihood of choosing this mode in Georgian Acres. However, in Table 17, this variable's coefficient remains negative but with a higher t-test statistic, signifying a more robust statistical significance for this relationship. Despite some variations in the statistical significance of certain variables, both tables consistently reveal the importance of cost, time, household characteristics, and gender in influencing mode choice decisions.

COMMUNITY HUB FOR SMART MOBILITY HUB SURVEY COMPARATIVE ANALYSIS

Two surveys were conducted at different stages to gauge the impact and effectiveness of this transit hub: the Pre-Hub Survey, conducted before the hub's implementation, and the Post-Hub Survey, carried out after the hub's construction. This comparative analysis delves into the insights obtained from the two surveys, shedding light on the perspectives and experiences of the Georgian Acres community concerning the transit network and the hub's influence on their daily travel patterns. The surveys sought to understand residents' feelings about the existing transit infrastructure and identified areas that required improvement. Additionally, the data collected provides valuable context on the community's transit struggles, enabling a comprehensive understanding of their needs and expectations from the newly implemented hub. Through this comparative analysis, we aim to gain insights into the changes in perceptions and experiences of the Georgian Acres community regarding their transit options before and after the hub's implementation. Understanding the hub's impact on residents' travel choices will be instrumental in enhancing the overall transportation system, ensuring that it aligns with the community's expectations and aspirations, and creating models that reflect the communities' experiences before and after the hub.

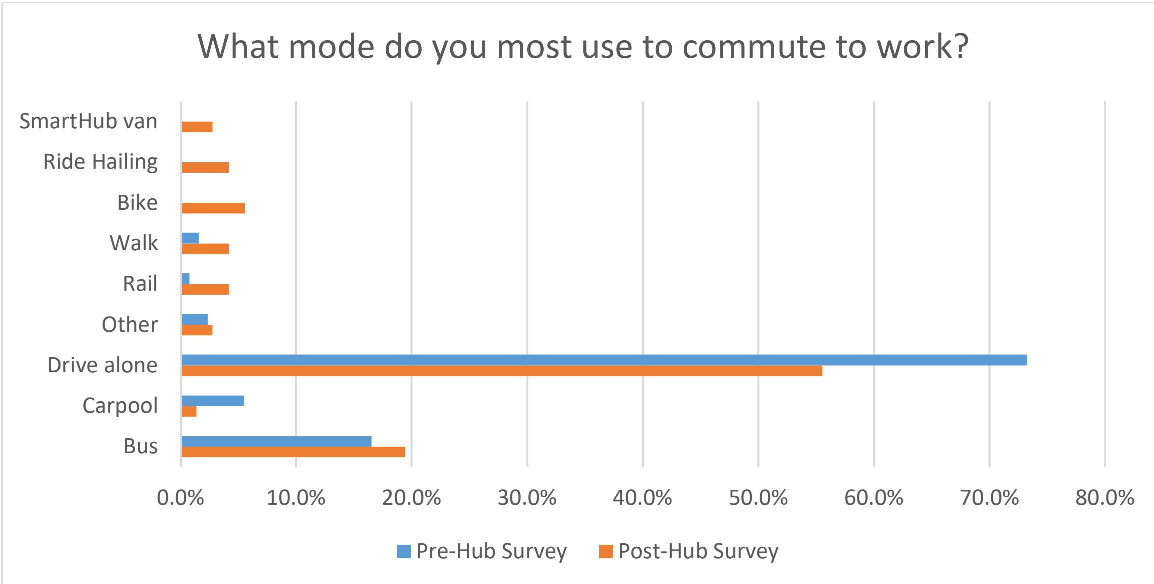


Figure: 14: Mode Used to Commute to Work - Pre-Hub vs Post-Hub Survey

Figure 14 shows the data presented in the Pre-Hub and Post-Hub Surveys regarding commuters' preferred mode of travel to work. Prior to the hub's implementation, the majority of respondents in the Georgian Acres community relied heavily on driving alone, accounting for 73.2% of the responses. However, there was a significant shift in mode preferences after the hub's construction. While driving alone remained the dominant choice, its percentage decreased to 55.6%, indicating a notable impact of the hub on commuting behavior. Notably, there was an increase in the preference for bus commuting, rising from 16.5% in the Pre-Hub Survey to 19.4% in the Post-Hub Survey. Moreover, rail, walk, bike, and ride-hailing options also experienced positive shifts, suggesting that the hub's presence has encouraged greater usage of alternative transportation modes. The data illustrates that the hub has positively influenced commuters' choices, diversifying their mode preferences and encouraging a more sustainable and efficient transit behavior in the Georgian Acres community.

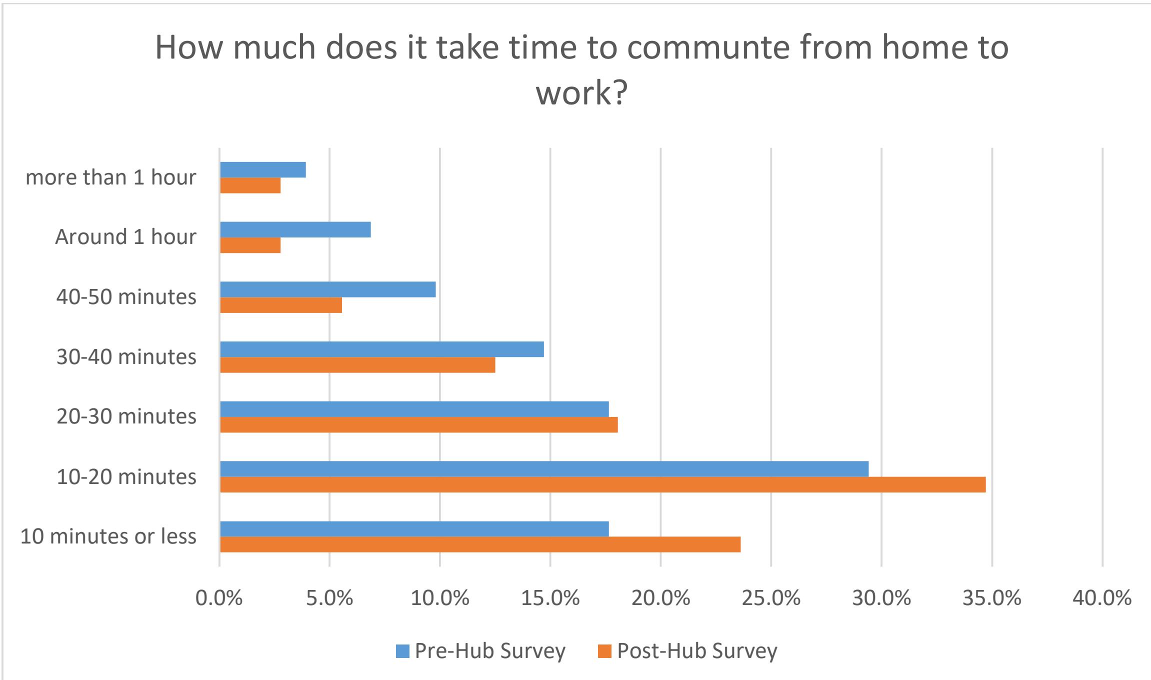


Figure 15: Time to Commute to Work - Pre-Hub vs Post-Hub Survey

The data presented in Figure 15 shows the commuters' reported commute times to work Pre-Hub and Post-Hub; this helps to understand the hub's impact on travel durations in the Georgian Acres community. Before the hub's implementation, a substantial proportion of respondents (29.4%) reported commute times between 10 to 20 minutes, while 17.6% had 10 minutes or less commutes. Following the hub's construction, there was a noticeable increase in the percentage of respondents with shorter commute times. Specifically, the proportion of individuals with 10 minutes or fewer commutes rose to 23.6%, and those with commutes in the 10 to 20 minutes range increased to 34.7%.

Moreover, the percentage of respondents with longer commute times of 40-50 minutes and around 1 hour decreased significantly, indicating that the hub has positively influenced travel efficiency and reduced commute durations for a considerable segment of the community. The data showcases the hub's potential to enhance accessibility and improve mobility in the Georgian Acres area, leading to more convenient and time-efficient commutes for many residents.

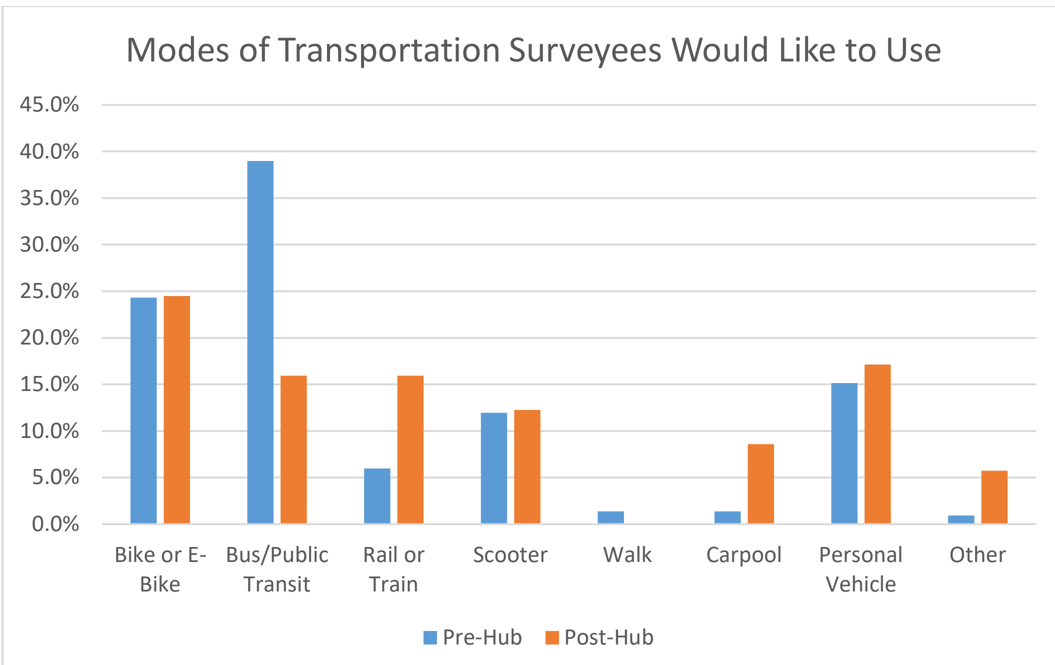


Figure: 17: Mode of Transit Respondents Would Like to Have More Accessible - Pre-Hub vs Post-Hub Survey

Figure 17 shows the respondents' preferences for more accessible transit modes in the Pre-Hub and Post-Hub Surveys. Before the hub's existence, most respondents (39.0%) expressed a desire for improved accessibility to bus/public transit options, indicating a demand for enhanced public transportation services. However, after the hub's construction, there was a notable decline in the preference for bus/public transit accessibility, dropping to 15.9%. Conversely, the desire for improved access to rail or train services increased substantially from 6.0% in the Pre-Hub Survey to 15.9% in the Post-Hub Survey, suggesting a positive response to the newly introduced transit options. Respondent's interest in carpooling as a more accessible mode also increased from 1.4% to 8.6%. While preferences for bike or e-bike accessibility remained relatively stable, the desire for scooter and personal vehicle accessibility also experienced slight growth. The data indicates that the hub has influenced respondents' transit preferences, leading to a greater interest in alternative transportation options and potentially promoting more sustainable commuting behaviors.

Based on the data presented in both Pre-Hub and Post-Hub Surveys, a comprehensive analysis of respondents' access modes to reach the bus stop reveals interesting insights about the hub's impact on travel behaviors. In the Post-Hub Survey, it is evident that the hub has facilitated a shift in access mode preferences among transit users in the Georgian Acres community. Notably, a significant number of respondents (75) reported walking as their primary mode of access to the bus stop, highlighting the importance of pedestrian infrastructure and last-mile connectivity in enhancing accessibility to public transit.

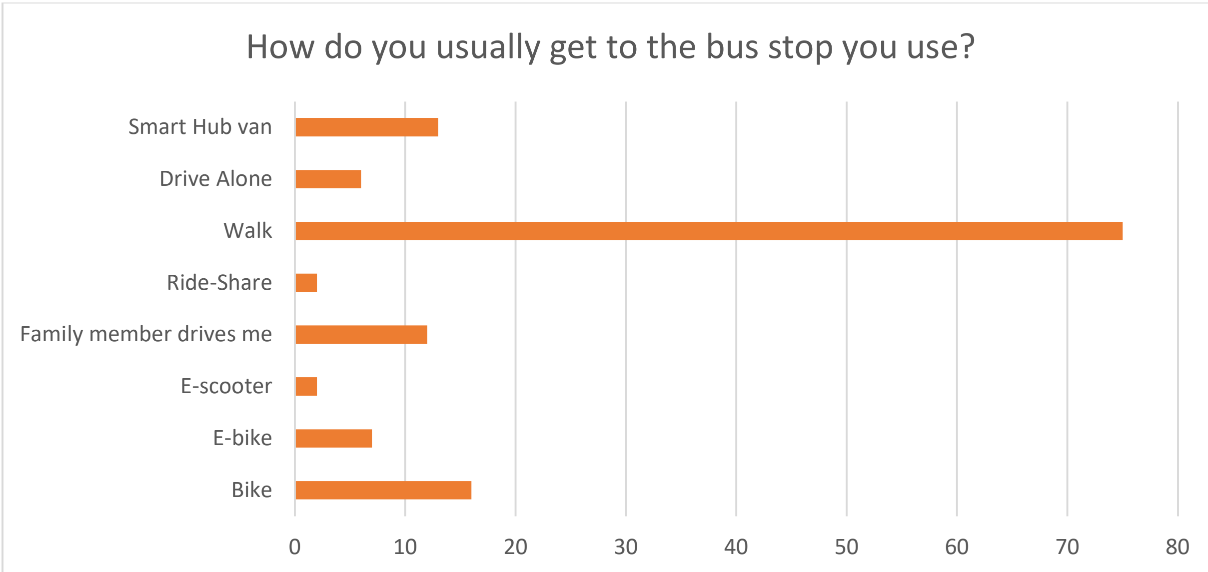


Figure: 18: Access Mode to the Bus Stop - Post-Hub Survey

Additionally, the availability of Smart Hub van services has attracted 13 respondents, showcasing the effectiveness of shared mobility in addressing access to public transit. Furthermore, biking and e-biking have emerged as popular options for reaching the bus stop, with 16 and 7 respondents suggesting that the hub's integration with cycling infrastructure has encouraged the adoption of active transportation modes. While the data provides valuable insights into access mode preferences after the hub's implementation, further analysis could benefit from a more extensive survey period and larger sample size to better understand the long-term impact of the hub on transit access behaviors in the Georgian Acres community.

Chapter 6: Discussion and Future Research

In conclusion, the findings from the Austin Travel Survey highlight the significant importance of access mode to transit users in shaping their travel behavior and overall transit experience. Access mode plays an important role in determining public transit's convenience, efficiency, and attractiveness. The survey data revealed that respondents' preferences for improved accessibility to various modes, such as buses, trains, bikes, and carpooling, reflect transit users' diverse needs and priorities. Understanding and addressing these access mode preferences are essential for designing a comprehensive and user-centric transit hub that effectively meets the community's mobility needs and encourages sustainable travel choices.

Based on the analysis of the Pre-Hub and Post-Hub surveys, the implementation of the hub has resulted in notable changes in commuting patterns, respondents' desired modes of transit, and commute times for the residents.

- There has been a notable increase in the preference for bus commuting, accompanied by rises in rail, walk, bike, and ride-hailing options in commuting to work. This shift indicates that the hub has effectively diversified the community's mode preferences, encouraging varied transportation choices.
- The percentage of respondents with shorter commute times (e.g., 10-20 minutes) increased significantly, while the proportion of individuals with longer commute times decreased notably. This improvement in travel efficiency showcases the hub's success

in enhancing accessibility and reducing commute durations for a considerable segment of the community.

- While there was a decline in the preference for bus/public transit accessibility, there was a substantial increase in the desire for improved access to rail or train services. The interest in carpooling also experienced significant growth, indicating the hub's influence on promoting more sustainable and collaborative transit options.

Using the data gathered from the Post-Hub Survey on access mode and insights from the mode choice model, the significance of walking as an access mode for Georgian Acres residents is evident in both. The mode choice model reveals that the variable "FemaleWalkAcc" has a negative coefficient, indicating that female respondents with bus access through walking have a slightly lower likelihood of choosing this mode. The findings from the Post-Hub Survey further underscore the importance of walking as an access mode. The survey results indicate that a substantial 56% of trips to the bus stop are made using walking. This data reflects a firm reliance on walking to access public transit. The patterns revealed in the mode choice model, and the results of the Post-Hub Survey collectively support the significance of walking as an access mode for GA residents and its influence on overall mode choice decisions.

The data collectively demonstrates that the hub has positively shaped the Georgian Acres' transportation landscape. It has facilitated more diverse and efficient commuting choices, reduced travel times for many residents, and influenced preferences toward sustainable transportation alternatives. The findings underscore the importance of such transit infrastructure in enhancing the overall quality of life and mobility for the residents of Georgian Acres. The survey's prevalence of walking trips to the bus stop demonstrates the practicality and desirability of pedestrian access to public transit services. It suggests that implementing the Smart Mobility Hub in GA has effectively encouraged walkability and accessibility to public transit. As cities strive to create sustainable and equitable transportation systems, understanding the significance of walking and micro-transit as an access mode is crucial. Integrating infrastructure that enables access modes, such as mobility hubs, can enhance the connectivity between neighborhoods and public transit services, making it more viable for residents to use transit. Continued feedback from the community will be essential to ensure that the hub's benefits are sustained, and further research can help so that hubs become more common for many neighborhoods in Austin to connect to the more extensive network.

LIMITATIONS

It is valuable to acknowledge the limitations of this study, including the Austin Travel Survey and travel surveys in general, particularly concerning data collection on access mode. Due to several factors, access mode data can be challenging to obtain in travel surveys. First, respondents may not always accurately report their access mode, leading to potential data inaccuracies. Additionally, access mode information may not be collected for all transit trips, limiting the completeness of the dataset. Moreover, travel surveys often focus on the primary mode of transportation during the main trip, which may not fully capture the nuances of access modes used for reaching transit stops. In order to overcome limitations, future travel surveys should consider using more comprehensive data collection methods like real-time tracking, GPS technologies, and mobile applications to gather detailed information on access mode choices. Additionally, integrating access mode questions into the survey design more explicitly can provide a better understanding of the factors influencing transit users' access decisions to better model transit behavior.

While the Pre-Hub and Post-Hub surveys provide valuable insights into the impact of the hub on the survey respondents' community in Georgian Acres, it is necessary to acknowledge certain limitations that may affect the findings. One limitation stems from the relatively small sample size in both the Pre-Hub and Post-Hub Surveys. With 200 validated respondents in the Pre-Hub Survey and 156 in the Post-Hub Survey, the sample size might not fully represent the entire community's diverse perspectives and experiences. A larger, more diverse sample could provide a more comprehensive understanding of the community's transit needs and preferences. Additionally, the time frame of the surveying, conducted from February to April 2023 for the Post-Hub Survey, may limit the study's ability to capture potential longer-term impacts of the hub on travel behavior and attitudes. A more extended observation period would allow for a more robust analysis of sustained changes in commuting patterns and mode choices over time due to the hub. Another significant limitation of the Pre-Hub Survey is the absence of information on respondents' access mode to the bus stop. This lack of data on access mode in the Pre-Hub Survey creates challenges when directly comparing it to the Post-Hub Survey, where access mode information was collected. Without access mode data in the Pre-Hub Survey, it becomes difficult to gauge the baseline pattern of how respondents accessed the bus stop before the hub's implementation, which limits the ability to fully understand how the hub may have influenced any shifts in access mode choices after the hub's implementation. These limitations may make it challenging to attribute changes in access mode preferences solely to the hub, as other external factors could also be influencing transit users' access choices. Despite these limitations, the study's findings remain valuable in providing a starting point for understanding the hub's effects on the surveyed community, warranting further research with a more extensive and extended data collection effort to draw more comprehensive conclusions.

FUTURE RESEARCH

Overall, recognizing the importance of access mode to transit users and addressing the limitations in data collection are crucial steps in enhancing the planning and design of transit systems and hubs that cater to the diverse needs and preferences of the community. By prioritizing access mode considerations, transit agencies, and policymakers can foster a more seamless and accessible transit experience, encourage greater public transit usage and promote sustainable, efficient transportation options. The project's focus on creating a base model for Austin's Georgian Acres neighborhood offers a valuable opportunity to study the hub's impact on an underserved community. The findings of this case study could pave the way for establishing additional Smart Mobility Hubs across the Austin area, creating a robust network of shared mobility options. Furthermore, in the broader context of Smart Cities, understanding the hub's role in fostering shared mobility, enhancing accessibility, and promoting sustainable transportation practices becomes essential for designing efficient and equitable urban transportation systems. As society increasingly prioritizes sustainable and mobile lifestyles, the development of cities becomes ever more critical. The research findings presented here can serve as valuable inputs for policymakers and infrastructure planners alike, paving the way for Smart Cities prioritizing shared mobility, accessibility, and sustainable development. Mobility hubs hold the potential to revolutionize transportation in urban areas, particularly in neighborhoods facing the first-mile problem of public transit accessibility. Further research into the impact of such hubs on residents' mobility patterns and their ability to address accessibility challenges at both community and city levels is warranted. Additionally, augmenting the range of access modes available could offer a promising solution to the first and last-mile transportation problem.

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