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INFLUENCING TRAVEL BEHAVIOR VIA AN OPEN-SOURCE PLATFORM PHASE 2

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16. Abstract

This project uses the open-source platform OneBusAway (OBA) developed at USF to explore strategies that can influence travel behavior to increase transit ridership. OneBusAway currently provides real-time transit information to users on a full range of devices and communication platforms, such as mobile apps, and serves more than 400,000 individuals across ten cities in the United States. The UPRM NICR team, with the support of USF developers of OBA, coordinated Phase One activities to implement OneBusAway on the Mayagüez Integrated Transportation System (TIM, for its acronym in Spanish). In Phase Two, georeference data corresponding to the transit systems' influence area was collected and recorded in a geographic database. Further data was obtained from focus groups, ridership studies, and a travel survey. Statistical and econometric methods were used to analyze the survey and focus groups and to determine factors influencing travel preferences. Spatial econometric models were estimated using all the collected data. The spatial correlation analysis indicated a weak positive spatial correlation, suggesting a slight clustering trend. Spatial regression analysis revealed that the number of stops in the area, vehicle ownership, and multiple stops positively influence transit use, while higher average age and median household income negatively impact boarding. Based on the activities conducted in this study, various strategies are integrated to increase transit ridership and contribute to reducing traffic congestion.

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Abbreviations and Acronyms

RTPI	Real-Time Passenger Information
TIM	Integrated Transit System of Mayagüez
NTDB	National Transit Database
FTA	Federal Transit Administration
OBA	OneBusAway
GTFS	General Transit Feed Specification
GPS	Global Positioning System
NICR	National Institute for Congestion Reduction
TNC	Transportation Network Companies
ICT	Information and Communication Technologies
GWPR	Geographically Weighted and Geographically Weighted Poisson
GWR	Geographically Weighted Regression
BSIZ	Bus Stop Influence Zone
USF	University of South Florida
API	Application Programming Interface
OLS	Ordinary Least Squares
GLM	Generalized Linear Model
SLX	Spatially Lagged X Model

Executive Summary

This research project was undertaken with the primary objectives of implementing a public transportation application, the One Bus Away (OBA) open-source platform, in Mayagüez’s Integrated Transit System (TIM) and assessing its impact on ridership. The project also aimed to analyze traveler behavior and develop strategies to increase the transit system’s ridership over private vehicles and other transportation methods in Mayagüez, Puerto Rico.

The project was divided into four main tasks: data collection to understand the Mayaguez transit system, ridership data analysis, modeling and analysis of OBA data, and developing strategies to influence travel behavior. The initial step included gathering information to characterize the Mayaguez transit system. Two focus groups and one comprehensive survey were conducted.

During the phase one implementation of the OBA software, significant improvements were made. These included fixing the active state of the tracking services and updating OBA to the latest version available.The performance of the OBA platform was enhanced using a Docker container, which increased the server stability and reduced downtime. These improvements significantly enhanced the accuracy of bus arrival predictions, thereby increasing user satisfaction and trust in the system.

The survey yielded significant information. Most survey participants were young adults (18-24) and older adults (65-85). The survey results indicated that non-users of the transit system were willing to consider leaving their private vehicles at home and using transit if they had available a reliable, efficient, and effective transit system with a very good real-time passenger information (RTPI) system and excellent conditions of the infrastructure including sheltered transit stops. The spatial analysis uncovered key factors influencing ridership, including stop location, vehicle ownership, median age, and median household income. Users found real-time predictions helpful in planning their trips. However, security concerns at bus stops and limited operating hours were considered potential barriers to increased transit use.

The statistical analysis showed a positive correlation between population size, number of households, and vehicle ownership. Negative correlations were seen between median age and population density. The spatial correlation analysis indicated a weak positive spatial correlation, suggesting a slight clustering trend. Spatial regression analysis revealed that the number of stops in the area, vehicle ownership, and multiple stops positively influence transit use, while higher average age and median household income negatively impact boarding.

The study concluded that real-time passenger information systems like OBA can improve public transport efficiency and user satisfaction. However, more exhaustive data collection is needed to account for other spatial variables that may influence boarding and the transition from private cars to public transit, thereby reducing congestion. Several strategies were recommended to improve public transit use in Mayaguez based on the information found. The following aspects summarize the main strategies. There is a need for a user-centered restructuring of the transit network, including trunk routes with dedicated right-of-way points that reach high economic and social activities. Increased operating hours and expanded routes to cover more points of interest. Enhancing safety features and amenities for bus stops and services. An increased awareness campaign about the transit system and the benefits of using the OBA application. The OBA platform's implementation in Mayagüez's transit system showed significant potential to improve public transportation efficiency and ridership by providing real-time information and addressing the potential users' desire for a reliable transit system.

Chapter 1. Introduction

Review of Previous Work

This report corresponds to phase two of the NICR project Influencing Travel Behavior via an Open-Source Platform. Previous work in phase one aimed to implement the open-source platform OneBusAway (OBA) in the Mayaguez Transit System (TIM, for its acronym in Spanish) to have a real-time passenger information (RTPI) system (Watkins et al., 2013) readily available for modeling and studying its impact on ridership. OBA provides real-time passenger information through a smartphone application. This information is provided by servers that use the General Transit Feed Specification (GTFS) files and the real-time vehicle location (i.e., Global Positioning System - GPS) to analyze and predict the arrival time of the transit vehicles at each bus stop.

TIM is a free bus service operating urban and rural routes within the most populated areas of the Municipality of Mayagüez, Puerto Rico. The TIM covers 52 square miles of the municipality and serves a population of 71,264 inhabitants. According to the FTA National Transit Database, TIM registered 188,407 Annual Unlinked Trips in 2019, or the equivalent of 725 daily trips (NTDB, 2019).

Phase I included a description of the Mayaguez municipality and its transit system. A demographic profile includes maps showing the neighborhoods' location, population density distribution, and traffic congestion conditions. The characteristics of the transportation and activity systems are presented in detail. A literature review was conducted, including congestion reduction strategies for transit, strategies for improving transit systems, and the description of the open-source platform OneBusAway (OBA) and the suite of programs required to implement it, including Traccar and Transit Clock.

Previous work also included understanding OBA and its components and generating the General Transit Feed Specification (GTFS) files required to implement OBA in the Mayaguez Transit System (TIM). Much work was devoted to testing GTFS files to ensure that OBA interpreted the transit lines correctly. Besides, many testing processes were performed to select the GPS device that was selected and to connect each one of the software components to implement OBA.

The primary outcome of the work performed in phase one was the successful implementation of OBA in the transit system of Mayaguez City. Preliminary results indicated that OBA accurately identified all system routes, and correctly predicted arrival times at specific stops while the buses were in operation. However, it is important to note that the project was ongoing, and as such, minor adjustments were required at the beginning of Phase two. These adjustments, presented in this report, underscore the need for continuous improvement in the transit system.

Phase II

Following the implementation of the OneBusAway server in Mayagüez, efforts were focused on enhancing performance and reducing server latency. At first, memory management errors occurred during runtime, resulting in problems for user traffic as the server could not handle load reduction when multiple users were active, leading to potential software crashes. During the first year, memory leaks and some code complications caused the servers to reach max memory capacity periodically, daily to weekly. These complications caused the servers to crash, causing little sustainability for software production. After debugging, the hosted services were separated by servers to improve their performance. The computer programs implemented were Traccar for GPS location tracking, Transit Clock for location prediction, and One Bus Away to handle data visualization.

Over the year, the servers hosting One Bus Away, Transit Clock, Traccar, and their respective databases received a new software architecture upgrade. After the services were implemented as a Docker container service, the servers achieved complete run time stability, with memory adjustments extending the container runtime duration. While implementing the software in Digital Ocean cloud servers, an Apache security system was included to comply with Hypertext Transfer Protocol Secure (HTTPS) security requirements. The main improvement over the previous year's version of OBA was the upgrade to OBA V2.x. By hosting the newly released versions of OBA, the servers had more uptime and did not max out the server capacities.

The running services communicated with each other through a Representational State Transfer (REST) application programming interface (API), functioning as a communication endpoint for other apps. For example, the Mayagüez OBA services communicate with the OBA mobile host, which receives our data. Dividing the software into containers enhances flexibility, allowing the code to be used as a data bridge for new mobile apps or websites. The developed REST API also includes functionality to store basic authentication and connection tokens for client activity, enabling external applications to directly connect to the developed services and have their historical activity recorded.

The research team's efforts did not stop at implementing the OneBusAway server in Mayagüez and assessing its performance. The team conducted a detailed analysis in phase two, leveraging boarding data from the route operator, census data from the United States Census Bureau, and area information around the bus stops. This comprehensive approach allowed us to devise strategies to influence travel behavior using OneBusAway or similar real-time information systems.

Chapter 2. Literature Review

Cities worldwide continue experiencing high levels of congestion with undesired consequences for the environment, the economy, the quality of life, and human health. Public transportation is often considered an alternative to restructuring city mobility, considering its advantages over other transportation methods (Bennett, 2023). Transit constitutes a better solution for the scarcity of public space, particularly in urban centers. Several mobility master plans incorporate public transportation systems to recover and improve the public space (Uspalyte-Vitkuniene et al., 2008), reorganize the city growth, and restructure the mobility as a whole considering their social, economic, and environmental sustainability goals.

The implementation and optimization of cities' transit systems have been deemed effective and sustainable alternatives to improve urban mobility (Moller et al., 2009; Duarte, 2009; Chiang et al., 2011; Chen et al., 2014; Eliasson y Proost, 2015). However, transit ridership has declined in many US cities, even before the COVID-19 Pandemic (Taylor et al., 2020; Watkins et al., 2020). According to the Federal Transit Administration, non-rail ridership decreased by 8.4% from 2010 to 2019 (FTA, 2019). In addition, unreliable, or inefficient transit systems could lead to low ridership (Beaudoin et al., 2017). Therefore, there is a need to generate new strategies to reverse the declining trend. One of these strategies is to provide users with real-time transit data through a real-time passenger information (RTPI) system. Implementing advanced technologies (such as Advanced Vehicle Location (AVL) and RTPI systems) allows us to look for new alternatives to increase ridership and improve public transportation efficiency. These technologies allow passengers to track the real-time location and arrival time of buses. Transit users can then utilize this information to their advantage and comfort by reducing actual waiting times and the perception of waiting time at the stop. This solution increases ridership by improving the riders' experience when using this service (Beaudoin et al., 2017).

RTPI systems with GPS and mobile applications for monitoring public transport have been explored in many cities. The combined use of satellite positioning, digital mapping, and route guidance has become widely used for road travel, leading to greater reliability in bus services and decreased waiting times at stops. However, its overall impact must still be fully understood (Metz and Metz, 2022). A prominent example of a successful real-time transit application is Unlocked Maps. This project implemented software like OneBusAway, using web virtualization to render real-time urban traffic station data. An application using fuzzy logic was developed as a guidance system, addressing dark areas in cities with high building density by integrating BLE beacons into their tracking system. This integration caused some false events due to the intensity of overlapping beacons. However, implementing fuzzy logic allowed the researchers to adapt the app and predict user actions during journeys (Molina-Gil et al., 2022). Their algorithms interpreted bus movement and informed users of the bus state. Although this method can be used to develop a system focusing on user action prediction, the OBA and OBA Mayagüez approach emphasizes open-source accessibility through a REST API for numerous uses. By merging multiple services of code, the fuzzy algorithm approach was implemented through an open-source solution with Transit Clock.

Several studies have explored the relationship between real-time transit information and transit system performance. Researchers like Zhang et al. (2008) utilize demand models or spatial economic models. For instance, Zhang et al. used data from the 2006–2007 University of Maryland campus transportation panel survey to demonstrate that real-time information significantly enhances passengers' sense of security when riding buses at night and increases overall satisfaction. Knowing public vehicle arrival times in advance could reduce passengers' waiting times of and attract more riders to use public transport (Ma et al., 2019). In addition, RTPI systems' performance has significantly benefited passengers by reducing their waiting times and decreasing anxiety levels and frustration when waiting for the bus (Brakewood et al., 2014). However, RTPI systems' performance alone has been found to produce narrow results in ridership increases (Tang and Thakuriah, 2012; Taylor et al., 2013). Therefore, a holistic set of strategies is required to tackle this problem, and real-time information provided to users plays a central role.

Many actors intervene in a transit system, and each one with their objectives should be considered while developing city transportation plans: The transportation authority, the operator, the users, and non-users intervene in a transit system (Manheim, 1979). For example, the users have various needs that differ according to their socio-economic and cultural characteristics (Chamseddine et al.,2020). Transit systems have captive riders and choice riders. Several strategies have been developed to attract choice riders. However, there is another group: potential riders. These potential passengers for the transit system may not be traveling because the transit system is not perceived as a viable alternative for their trips. For example, young riders could navigate the system if they had enough information to use it. It is necessary to detect these kinds of opportunities to attract riders to our transit systems. Spatial analysis considering the characteristics of the population in the transit service area and beyond has the potential to find these types of relationships, detect opportunities, and promote strategies to incentivize the use of transit in a particular region.

An essential step in generating city transportation plans is the development of travel demand models. A new set of models that have been incorporated to explore travel demand includes spatial correlation models to complement the classic trip generation and attraction models. The classic models include several variables and methods to estimate the number of trips per area. These factors include the city population, income, vehicle ownership, and economic activity. Once the trip estimates by area are obtained, an Origin-Destination matrix is created to determine the project's allocation model and corresponding demand model. The travel assignment model requires defining the characteristics of the transportation network and the areas for trip estimates. Larger study areas will generate more accurate results. Once these areas are established, information from each one is associated with its centroid, and the centroid is linked to the network. This data is then distributed across a transportation network composed of links and nodes. Finally, traffic assignment models for different modes are used to allocate the trips in the study area (Ortúzar and Willumsen (2011)).

Spatial correlation models use many of the variables considered in the classic model, plus all the information that can be geo-referenced in the vicinity of bus stops along the transit routes. According to Pitombo et al. (2015), despite the current wide availability of geo-referenced information and the emergence of Spatial Travel Demand Analysis as a research field, only a few studies have integrated mode choice modeling methods and geographical information. (Mueller and Weiler, 2023), using a combination of travel, employment, and built environment datasets from Denver, Colorado, found that environmental variables have a limited association with transportation mode choice and underscored the benefits of formal spatial modeling to other demand models. (Marques and Pitombo, 2023) propose comparing approaches for modeling transit ridership at the bus stop level, employing linear, Poisson, Geographically Weighted Regression (GWR), and Geographically Weighted Poisson Regression (GWPR). The results from goodness-of-fit measures confirmed the assumption that adding asymmetry and spatial autocorrelation, individually and together, into transportation demand modeling gradually improves estimation accuracy.

Pan et al. (2019) conducted a study using a geographically weighted regression (GWR) model to establish a connection between the length of the bus stop influence zone (BSIZ) and multiple contributing factors. Their findings revealed that urban morphology plays a pivotal role in determining the length of BSIZ, showing pronounced spatial variations. Significant influences on the length of BSIZ included the density of businesses near bus stops, proximity to intersections, road classification, availability of public amenities, bus queue lengths, and traffic volume.

The use of GPS and mobile applications to monitor public transport, combined with the analysis of spatial regression models, offers a comprehensive approach to improving and enhancing the efficiency of public transport and reducing urban traffic congestion. Generating new econometric and spatial transit demand models incorporating the characteristics of activity and transportation systems is an essential step in this comprehensive approach. Furthermore, aside from direct traffic congestion, spatial regression models that consider boarding patterns and socioeconomic characteristics of the population around bus stops can also provide valuable insights to enhance public transportation efficiency and reduce congestion. These models help identify patterns in public transport demand and shed light on how population density, income levels, and accessibility influence travel decisions. These technologies provide direct benefits to users through real-time information, allowing transport authorities to make more informed decisions about bus route planning and management, which can improve urban mobility.

Many additional strategies have been studied over the years. For example, Litman and their team found that enhancing the promotion and accessibility of public transportation systems can incentivize commuters to opt for transit or micro-mobility instead of private vehicles. This approach not only reduces individual car usage but also addresses traffic density issues in metropolitan areas (Litman and Litman, 2024). Implementing a Congestion Charging System (CCS) that aims to discourage the use of private vehicles with low passenger capacity significantly reduces traffic congestion (Gomez et al., 2024). Furthermore, promoting active transportation modes like walking, and micro-mobility like cycling, through infrastructure improvements can encourage healthier and more environmentally friendly commuting options (Handy et al., 2010). Another effective strategy involves promoting telework, which reduces the need for daily commuting as people who work exclusively remotely show less total mobility, thereby easing congestion during peak travel times (Wöhner, 2022). Integrating land use planning strategies that combine residential, commercial, and recreational areas, as density, land use diversity and pedestrian-oriented designs can minimize the distance people must travel to work, shopping, and leisure activities by reducing travel rates and encouraging non-car travel in a statistically significant manner. Consequently, decreasing overall congestion (Cervero and Kockelman, 1997). Finally, the implementation of the RTPI app to locate stops and see bus-time arrival in real time can incentivize the use of transit instead of the private car due to the reliability improvements that arise with real-time information.

Chapter 3. Methodology

This section describes the methodology developed for this study, divided into four phases: evaluating the effectiveness of OBA, conducting data collection activities, including a riders' survey, developing models and analyzing OBA data, and developing strategies to influence passenger travel behavior. Figure 1 presents a diagram depicting the main tasks in phase two of this project.

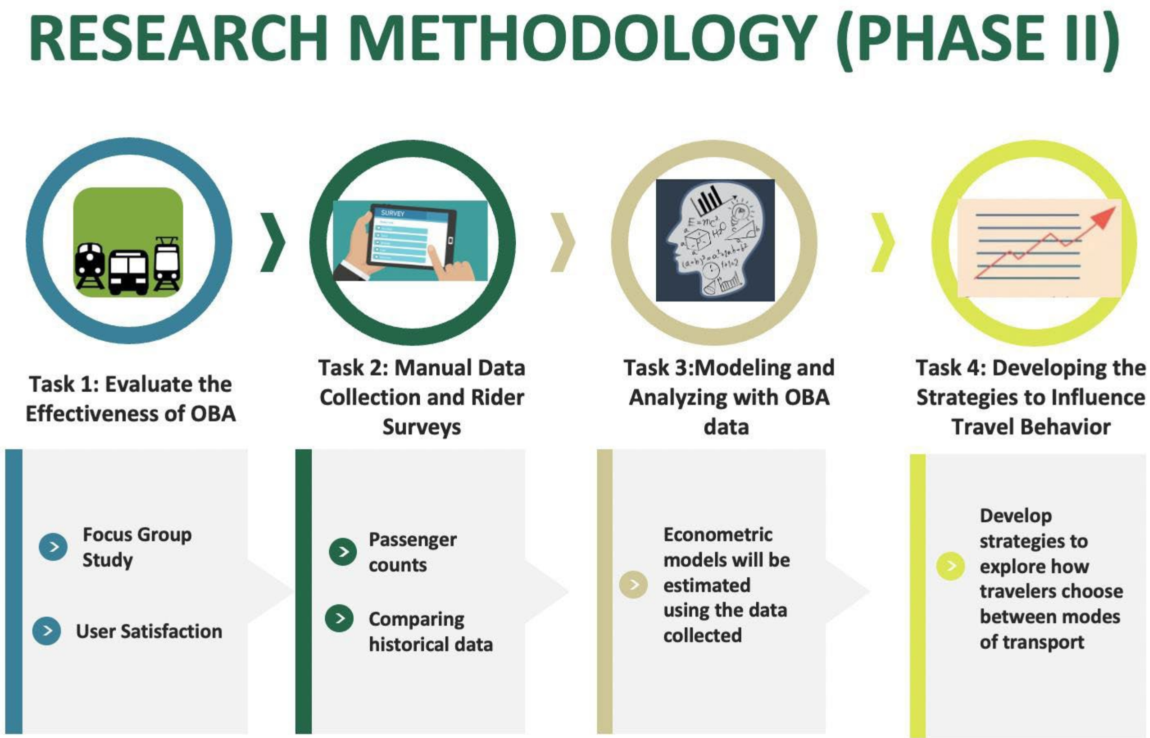


Figure 1. Research Methodology

The first task involves collecting and analyzing data to characterize the public transportation system in Mayagüez. This data collection effort includes two focus group sessions conducted with transit riders from the TIM transit system before survey developemnt and deployment. Additionally, a survey was administered two months after implementing OneBusAway. surveying passengers and potential users to gather insights about their demographics, travel preferences, motivations, perceptions of the transit system, and general decision-making processes, including origin-destination patterns. Tablets and specialized data collection software facilitated these data collection efforts.

The second task is to collect boarding data to determine ridership characteristics and distribution among the routes of the TIM system. The information was obtained from the TIM operator for one year of data collected before the COVID-19 Pandemic. Initially, an effort to conduct ridership studies was planned; however, given the restricted conditions of transit travel during the pandemic, those efforts were averted. Therefore, the ridership data was analyzed from one year of operator's data collected as part of their everyday operations. In addition, as part of this task, the research team also undertook an updated analysis of activity systems initially conducted in Phase One to integrate any modifications in the spatial distribution of critical activities linked to transit services.

The third task focused on modeling and analysis of OneBusAway data along with the data collected to understand the demand and the activity system. Econometric models were estimated using the data collected in previous tasks to study travel patterns, local public transportation habits, and their characteristics. The aim was to provide recommendations to decision-makers to improve the transit service, increase ridership, and reduce traffic congestion. The fourth and final task involved developing strategies to influence travelers' behavior. These tasks considered user behavior and system performance calculated using the open-source platform OBA data. A detailed explanation of the activities conducted in each task follows.

Task 1: Data collection to understand the Mayagüez transit system

Before Task 1

During the previous year of the implementation of OneBusAway. One of the key necessary fixes for the new development year was to fix the active state of the tracking services, update OneBusAway to its latest version and to set up a stable server for longer up times. With the focus on server enhancement, the OneBusAway server was set up and hosted in Digital Ocean. The cloud servers implemented had Apache HTTPS security for traffic communication. The software deployment was made using Docker and the OneBusAway documentation to automatically create a GTFS bundle and generate an instance.

OneBusAway Mayagüez

Once OneBusAway was implemented, it enabled the development of a new tool using its Application Programming Interface (API). To provide researchers and developers with active data about the app and its live status, an administrative webpage, and a second transit tracker were also developed. To identify the software outages and error logs generated by the server, it was important to implement the OBA API and a web scrapper to gather real-time data on the performance and activity of the various active services.

With the implementation of OneBusAway in Mayagüez, the second phase of development enhanced the software's accessibility to new features and flexibility in implementation. OneBusAway focuses on displaying traffic information in a user-friendly manner and handles a specific set of tasks. By the end of the second phase, OneBusAway was deployed in Mayagüez using Docker, which finalized all software used in containers within the servers. This advancement allowed the services to remain active for longer periods and helped reduce service downtime. The OneBusAway deployment was utilized by citizens in Mayagüez. The structural modifications made to the servers enabled the software to run for numerous weeks without reaching the memory or processing limit.

To facilitate data storage and retrieval from OBA and the other services, a REST API was implemented. REST API, short for Representational State Transfer, is an architecture style that allows data to be stored, read, and distributed over the web. Using a NodeJS server, the REST API was deployed.

In addition to OneBusAway, a second Transit Tracker app was developed using the OBA architecture and API. In contrast to OBA, this app was coded to run on both iOS and Android platforms, leveraging shared same source code. It extends the functionalities of the administrative web app and incorporates the capabilities of the REST API hosted on the server. The REST API will serve as the central data storage for information generated by the administrative web page and the implemented transit tracker. This setup enables features such as feedback forms and user-derived data. For example, features like user trip history and in-route feedback, which were previously unavailable, can now be implemented.

Focus Group and Survey

As part of evaluating the effectiveness of OBA and collecting manual data, the research team conducted two focus groups and one survey.

Focus Groups I

The purpose of the first focus group was to study the potential impact of the change in travel behavior following the implementation of OBA Mayagüez Beta. Ten frequent users of the Mayagüez transit system were recruited for this focus group. Participants were asked to download OBA on their smartphones and use the app for two weeks. Upon agreeing to participate in the study, each participant was provided with an instruction manual on using the OneBusAway smartphone application.

The participants then had two weeks to utilize the application in their daily travels. After this period, the research team met with all the participants to form the focus group. The participants' user experiences, opinions, and recommendations were documented during this session using written notes and audio recordings. The participants were asked to engage in the focus group discussion, where the following questions were posed:

1. Please describe your experiences when making your daily trips in the Mayagüez Integrated Transportation System.
    a. When you travel, where and from, the stops you use, the route, etc.
2. What was your experience in the learning process of using the application?
    a. Comments on the information that was delivered. (Was it helpful, and how can it be improved?)
3. How was the experience during the two weeks you used the application?
    a. Positive aspects
    b. negative aspects
4. Did you find the predictions helpful for your daily commute?
    a. How did you use the predictions?
5. Did you have any problems using the application?
    a. How did you solve it?
6. What were the benefits you found from using the app?
7. What should be clarified to the public when the application is implemented?
8. Before using the application, how did you plan your trip to take the bus?
9. With the application, how did you plan your trip to take the bus?
10. Additional Comments
11. Additional Recommendations

All the questions asked were open-ended, emphasizing the importance of the participants' feedback in shaping the future of OBA. This approach was taken in the hopes that the participants would further elaborate on their experience utilizing OBA.

Focus Groups II

The research team conducted a second focus group, recruiting 10 participants, different from the first group. In contrast to the first group, this focus group was composed of non-transit users.

The objectives of this focus group were:

- To document traveler behavior patterns and mode choice
- To determine if the application OneBusAway can influence travel behavior.

The following information was obtained from the participants in the focus group:

- Origin and Destination travel patterns
- Mode choice
- Experiences from the selective mode choice

- Opinions on the Mayagüez Transit System

The participants were asked a series of questions to ascertain the desired data.

Survey

A survey aimed at creating an accurate behavior model of the Mayagüez traveler was designed to collect travel behavior data from the population within the Mayagüez transit system area of influence. The primary objective of this study is to reduce congestion by encouraging the use of transit over private vehicles. The survey is tailored for both users and non-users of the transit system, with the exclusion of those without access to the transit system. Here, access to transit is defined as having the option to make a trip using transit. The survey is structured into three sections: demographic, typical travel patterns, and potential for pattern change.

The first section collects basic demographic information such as the nearest bus stop, gender, age, private vehicle ownership, and annual income. The objective is to understand the population and identify captive transit users, those who have no other means of travel. The survey was directed at both users (captive and non-captive) and non-users of the local transit system.

The second section aims to understand the participants' travel patterns, including when they typically leave their houses, where they go, and what activities generate these trips. Also, in this section users were asked to give a rating from 1 to 10 to the stops that were closest to their place of residence, with 1 being the lowest rating and 10 being the highest. They were also instructed to rank the characteristics of the stops according to importance, including lighting, security, and shelter conditions, among others.

The third section includes questions about whether the participants would be more likely to use transit if provided with a real-time passenger information syste m. It also asks about the participants' general use of smartphones to establish a baseline of their familiarity with using a smartphone application in their daily lives.

Task 2: Manual data collection and rider survey

Historical ridership data collection

Ridership data consisting of boarding counts of the system in PDF format, was provided by Sonnell, the operator of the rural routes. The data corresponds to the boarding information of all the system routes operating in 2019, including Route 102, 105, 106, 108, and Route 348. Additionally, Route 349 began operations in October 2019, so data for this route is only available for the last three months of 2019.

The digitalization process involved entering the information from the 2104 forms into an Excel spreadsheet. A rigorous review of the data entered was conducted to make sure that all the information available in paper was correctly digitized in the excel file. The digital information was analyzed and summarized using descriptive statistics methods and generating graphs of boardings by stops and direction of circulation, as well as to generate monthly and daily boarding averages.

Census data

Data on the characteristics of the population in the vicinity of the bus stop were collected from the Census Bureau website and also from the 2019 American Community Survey (ACS). The data obtained corresponds to the following variables Population (pop), Female, Male, Median Age (MedAge), household (HouseHold), Median household income (MHHoldInc), Vehicle Ownership (VehOwnersh), Vehicle per household (VehperHH), Percentage of Households with Cell (X.HHwCell), Percentage of Households with no Internet connection

(X.HHnoInter), and Percentage of Households with people older than 60 years old (X.HHmore60). Additionally, Median Age was categorized into three levels (young for age under 21, adult for age between 21 and 50, and elderly for age more than 50) renamed MedAgeCat, and Median Household Income was recorded as a categorical variable renamed MHHoldIncCat with three levels (low for income under US$25,000, mid for income between US$25,000 and US$75,000, and high for income more than US$75,000).

The data was processed to match the area surrounding the bus stop, also known as the area of influence or catchment area, as the original data was based on the census block area defined by the Puerto Rico Planning Board. Figure 2 shows an example that presents census blocks that include the stop areas corresponding to one of the transit routes. The square highlights three census blocks that coincide in a particular area. Each census block has a different color (green, light blue and yellow). Out of the three stops shown, the one in the center depicts the complete delineation of the corresponding stop area (StA). Besides, the buildings inside the delineated stop area are those included as the variable BuAStA.

The process to obtain data from a larger area to refer it to a smaller one was as follows:

- In the Block Area (BA), population characteristics such as population, gender, age, and income was obtained from ACS. The information for each variable was distributed into the Building Area (BuA) and then summarize them inside the Stop Area (StA), as shown in Figure 2.

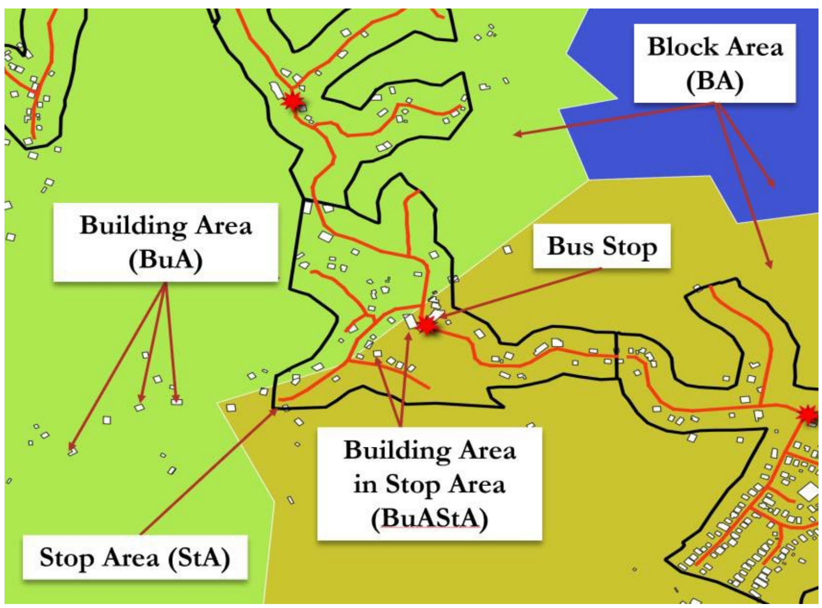


Figure 2. Area Delimitation

- If the variable being analyzed is an average variable, such as Median Household Income (MHHoldInc), the value of the BA is assigned to the corresponding variable for the StA. If the variable being analyzed is a total quantity variable like population, the assignment from BA to StA is carried out using the following equations:

    - **Variable of Block Area (VBA):**

$$VBA = Data$$

- **Building Area (BuA):**
  $$BuA = Measured\ Data$$

- **Proportion of Building Area (%BuA):**
  $$\%BuAi = \frac{BuA_i}{\sum BuA}$$

- **Variable in Building (VBu):**
  $$VBu = VBA\ x\ \%\ BuA$$

- **Variable in Stop Area (VStA):**
  $$VStA = \sum VBu_{inside\ StA}$$

- ***Example:***
  Population in Stop Area: $Population\ in\ StA = \sum Population\_Bu_{inside\ Sta}$

Where VBA is the variable obtained from ACS referenced to the block area, like population or income. BuA is the area of each building inside the Census Block Area. VBu is the variable in the building and represents the portion of the variable that corresponds to each building in the BA, and VSta is the summation of the variable of all the building inside the stop area (StA).

The outcome of this process is a matrix database that includes the characteristics of the bus stops areas of influence. This information can be enhanced with additional data to create statistical models that elucidate ridership or congestion. Figure 3 presents an example of the table results obtained following the method and equations presented above.

Area_ID	STOPID	RUTAID	Pop	Female	Male	MedAge	HouseHold	MHHoldInc	VehOwnersh	VehperHH	%HHwCell	%HHnoInter	%HHmore60
1	T01	T01	1279	360	599	27	524	3241	579	1.08	0.69	0.24	0.28
3	R102RS02-09	R102	1649	475	630	36	504	11134	513	0.96	0.48	0.34	0.47
4	R102RS08	R102	1130	536	499	34	413	10117	193	0.78	0.41	0.4	0.44
5	R102RS03-07	R102	2118	1303	726	23	702	2500	389	0.54	0.4	0.4	0.15
6	R102RS04	R102	362	167	135	52	123	18850	138	1.13	0.63	0.24	0.69
7	R102RS05	R102	304	115	124	44	72	32434	123	1.69	0.7	0.25	0.59
8	R102RS06	R102	1090	515	400	34	350	32434	605	1.72	0.66	0.1	0.47
10	R105RS04	R105	851	288	234	43	262	14515	303	1.21	0.47	0.43	0.53

Figure 3. Matrix Database

Data Collection of OBA

During this phase of the OBA development, a series of data collections were analyzed to further study how the OBA service performed. It is worth noting that 8 devices have been implemented into the transit system. The data collections from the connected devices are divided between devices, routes, and performance metrics. When gathering data from the connected devices, the following parameters are considered: latitude, longitude, speed, device time, server time, GPS accuracy, and distance. For routes, the data fields under analysis include predicted_time, actual_time, prediction_altitude, read_time, route, direction, trip, stop, vehicle_id, prediction_length_sec, next_stop, shape_id, direction.

OD Matrix

The online survey gathered information about the origins and destinations of the trips taken by the respondents. The information obtained was stored in a spreadsheet created using Google Forms and then manually processed to analyze the trip-related data. As a result of these processes and the gathered information, the data regarding origin and destination of the trips of the residents in the surveyed areas were identified. This information will be used to create an OD (origin-destination) matrix.

Task 3: Modeling and analysis of OneBusAway data coupled with the data gathered for the characterization of the demand and the activity system

Modeling and analyzing with OBA

The boarding data obtained from the operator, which was separated by bus stop, was combined with the information processed from the American Community Survey (ACS). The data was grouped by catchment or surrounding area. This process aims to conduct statistical analysis and create a spatial statistical model regression to understand the boarding at each bus stop. The overall procedure can be divided into four steps:

- Exploration data analysis (EDA).
- Lineal correlation.
- Spatial correlation
- Spatial Regression

Exploratory Data Analysis (EDA).

The procedure involves analyzing and investigating datasets to understand their main characteristics. This includes using methods to summarize and visualize data. Exploratory Data Analysis (EDA) helps in determining the best way to manage data to obtain the needed answers, discover patterns, detect anomalies, test hypotheses, or verify assumptions (IBM, 2024).

Lineal correlation.

The linear correlation can be measured using Pearson's correlation coefficient. This is an index that measures the degree of covariation between different linearly related variables. The correlation coefficient is easy to calculate and interpret (Alfonso Palmer et al., 2001). If we have two variables X and Y, and we define the Pearson correlation coefficient between these two variables as r_{xy} then:

$$-1 \leq r_{xy} \geq 1$$

Spatial correlation.

Spatial correlation is a descriptive statistical index that allows us to measure how the analyzed phenomena are distributed in geographic space (Goodchild, 1986). It measures the degree to which a geographic variable is correlated with itself in different areas (near or neighboring) of the study area. Figure 4 illustrates the possible results of spatial autocorrelation.

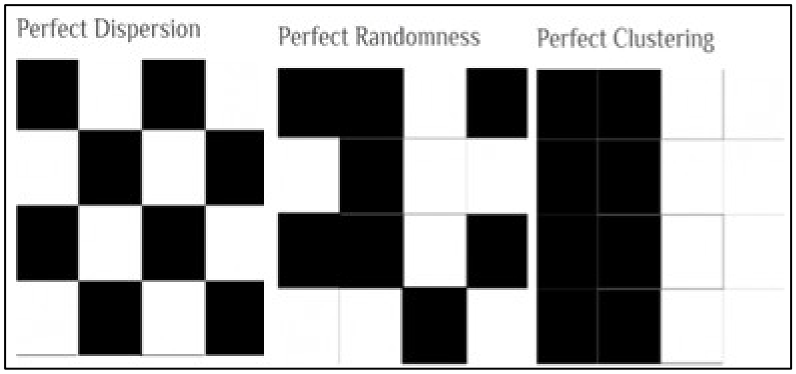


Figure 4. Spatial correlation possible results
Source: https://www.statisticshowto.com/morans-i/

The estimation of the spatial correlation is determined through the calculation of the *Moran Index (I),* as shown in Figure 4 using the following expression (Siabato et al., 2019) :

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Where:

I: Moran Index that indicates:
- A perfect dispersion (I = 0)
- A perfect randomness (I = -1)
- A perfect clustering (I = 1)

w_{ij}: neighborhood matrix.
x: studied variable.
x̄: mean studied variable.
i: variable index
j: variable neighbor index

The spatial correlation was calculated using as independet variable the boardings estimated from the data provided by the rural route operator for 2019. This data corresponds to passenger boardings in the bus stops. It must be noted that if a surrounding area contains several stops of different routes, the boardings in these areas will be added together.

Spatial Regression.

Spatial regression is a regression model that considers the geographical location of the variables. This procedure extends the traditional regression model, which only involves the explanatory variables of the response variable, by incorporating the spatial proximity of the variables. By doing this we can identify whether an explanatory variable from a given area influences the response variable in that same area, and if an explanatory variable from a neighboring area affects the behavior of the analyzed response variable.

The general procedure for defining spatial regression is to determine which model best fits the data. The first step is to estimate an Ordinary Least Squares (OLS), or a Generalized Linear Model (GLM) based on the variable type. Since the response variable is the bus stop boardings (counting variable), the recommended distribution is a Poisson or Negative Binomial. The second step is to estimate a spatial regression that provides a better fit for the data previously modeled with the OLS or GLM model. In the case of using count data, Wu and Chvosta (2016) recommend the Spatially Lagged X (SLX) model. This model only considers the influence of the neighboring explanatory variables on the response variable. The SLX model is defined as follows:

$$y = X\beta + W\theta + \varepsilon$$

Where:

y: response variable:
X: explanatory matrix variable.
W: neighboring matrix variable.
β, θ: calibration coefficients.
e: error.

Task 4: Developing the strategies to influence travel behavior

Strategies to influence travel behavior.

To influence travel behavior and choices, we can utilize various interventions that address several aspects of the travel system. These include making infrastructure improvements in the physical environment, enhancing transportation services, implementing policies and regulations such as pricing mechanisms, providing information, running education and awareness campaigns, as well as considering social and cultural factors through social marketing and incentives. By combining these interventions, a comprehensive and coherent approach can be created to achieve integrated effects and long-term impacts (Transportation Planning, 2024)**.**

To develop this task, the research team took into account the findings of the literature review, the focus group discussions, the survey conducted among transit system users and non-users, the spatial correlation analyses, and the creation of a spatial regression model in order to develop strategies that enhance the public transportation system and help to reduce traffic congestion in the transportation network.

Chapter 4. OBA Performance and Effectiveness Results

An enhancement from the previous year of OBA development is the OneBusAway active predictions and the improvements in server memory load. Graph 8 below shows the bandwidth for a running Docker container for a healthy running service. Throughout the year a series of modifications were made on how the route predictions accommodated the Mayaguez system, a result from 31 days of data from January 2023 can be reflected in Figure 5. This figure demonstrates the aggregated predictions made to a stop and with what accuracy is a prediction for arrival time given. The green section indicates that a vehicle arrived from 1minute to 4 minutes of the predicted time. The yellow section shows that a bus reached the destination after 4 minutes and finally if the section is red, it shows that the vehicle reached earlier than predicted. The indicator for early arrival is red because due to wrongful late predictions, a bus user will not be able to reach the bus stop on time. In a parallel comparison, the colors to describe Figure 6 represent similar things. The green section demonstrates the accuracy of predictions given and if the bus arrived earlier or later than the predicted time. On Figure 6, it can be shown how at 0 and 1 minutes the column is all green, this shows that a 100% of the time, when the prediction said the bus would be on the stop it was true. The further the predictions are made from the arrival stop the greater the error margin.

To better understand and visualize how the server communicated with each instance Figure 9 and Figure 10 reflect how the data is passed, and events occur. Figure 9 demonstrates how when a user interacts with OneBusAway it saves information in its local service but in addition it receives information from the Traccar and Transit Clock services. If any of the services stop working the prediction values will be null and only the itinerary will be shown. As a cloud service, when One Bus Away is running there are 3 main functions which need to be imported into the service. These are: 'gtfsRealTimeTrip', 'gtfsRealtimeAlerts', 'gtfsRealTimeUpdates'. The previous functions are the resources needed to start each One Bus Away instance. Due to the software running in servers each Docker container should restart if the output page causes an error, this helped keep the OneBusAway service active for longer.

For the predictions given for OneBusAway, for two weeks' worth of data from September 2022 the following conclusions can be drawn. On average, across all the active routes, the data is illustrated in Table 1.

Table 1. Arrival data time reported from OBA

Prediction Given	1 minute early	Within 1 minute	1 minutes late
On arrival	0%	86.2%	13.8%
5 minutes	43.2%	42.4%	14.4%
10 minutes	53.8%	30%	16.2%
15 minutes	80%	11.1%	8.9%

When considering data from both routes and devices, system metrics can be generated. As such the following datasets are generated to further study the routes.

1. GPS Accuracy Fluctuation Throughout Route: The route creates a paring system between the device location and route map, processing parameters for accuracy, speed, altitude, and predictions generated. For the Mayagüez system, which integrates both urban and rural areas within the bus system, it is important to note how the mountains, altitude, and weather affect the GPS accuracy throughout the

route. This study aims to demonstrate the extent to which these factors influence the predictions provided to users.
2. Arrival Time Error Range by Stop: Identify stops with a higher error range compared to others.
3. Determine how much time each vehicle stops on average through the routes.

Figure 5 and Figure 6 illustrate the performance of the transit helper app for 31 days (about 1 month) of recorded data. Before identifying the areas for improvement, it is necessary to mention the current state of the transit system. The OneBusAway software relies on a strict itinerary and fixed arrival times per stop to operate effectively. However, there are instances of special events or anomalies in Mayagüez that may lead to changes in bus routes or the order of stops. While these deviations are intended to accommodate special activities for a brief period, they result in inconsistencies that negatively impact the accuracy of arrival time predictions when analyzing the overall data.

Figure 5 reflects the scheduled adherence, which serves as the indicator for the operational efficiency recorded in the app. In the ongoing direction (Direction 0), it is observed that from the specified time on the GTFS itinerary, the bus arrives 4 minutes after the originally specified arrival hour 52% to 70% of the time. Figure 6 illustrates the performance of predictions on route 102 during the recorded month. The accuracy of predictions improved as the bus approached, while the error range widened as the bus was further away from arrival.

Figure 7 and Figure 8 below illustrate how one week of one bus away from receiving data is reflected. This data is from May 06, 2022, to May 13, 2022. Figure 7 illustrates a bandwidth peak of 90 kb/s while Figure 8 shows a regular bandwidth peak of 11 kb/s. Representing the regular bandwidth during the day for a service with no user activity but with active transit data generation. In Figure 7, which shows active users, peaks between 80 kb/s and 100 kb/s are observed. At times, these requests would reach peaks of 2mb/s. However, on these occasions, the program reached a memory limit. The diagrams provide a clear representation of the servers online with activity. With the One Bus Away v2.x running without memory leak bugs, a representation can be viewed on Figure 8.

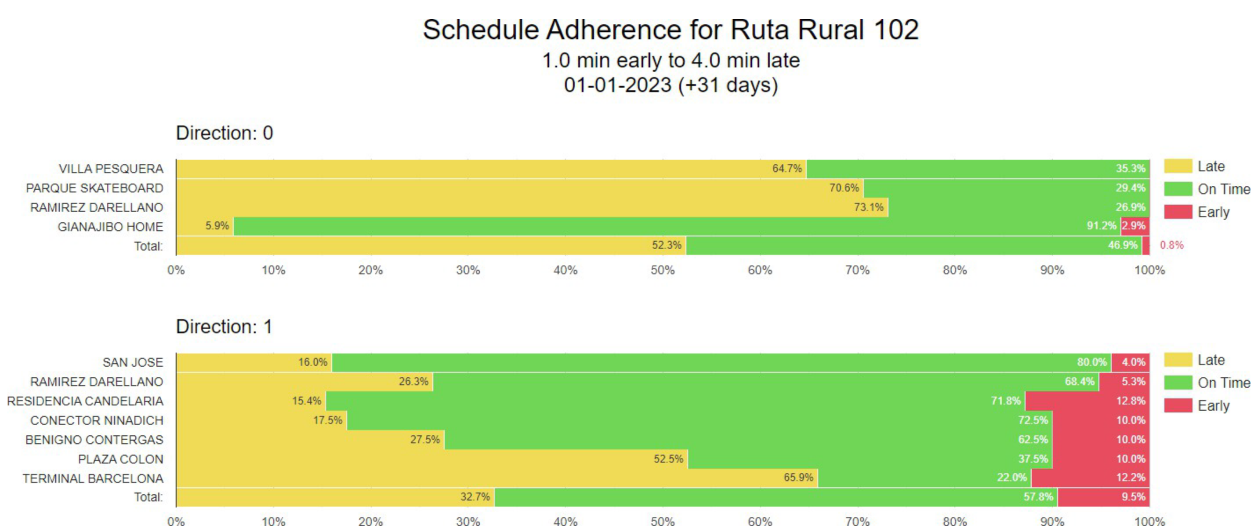


Figure 5. Schedule Adherence data for route 102

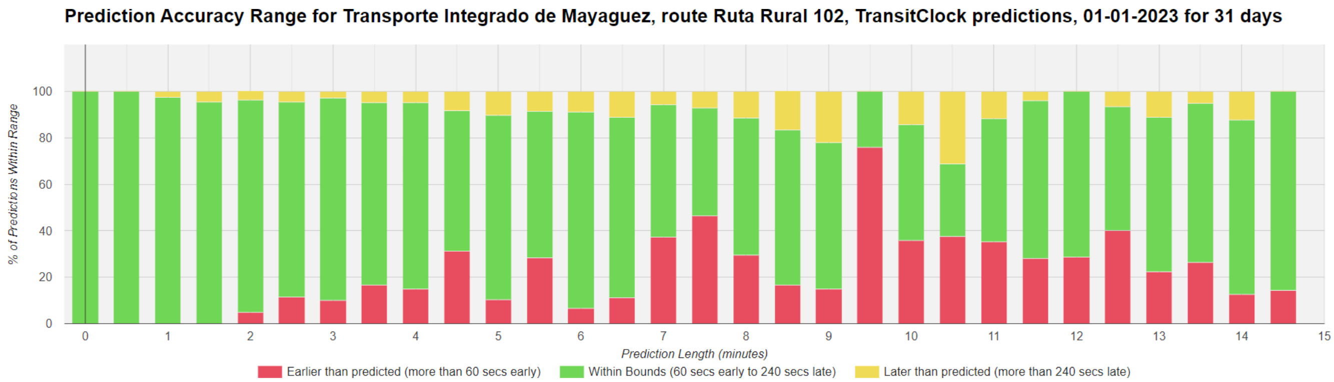


Figure 6. Prediction Accuracy data for route 102

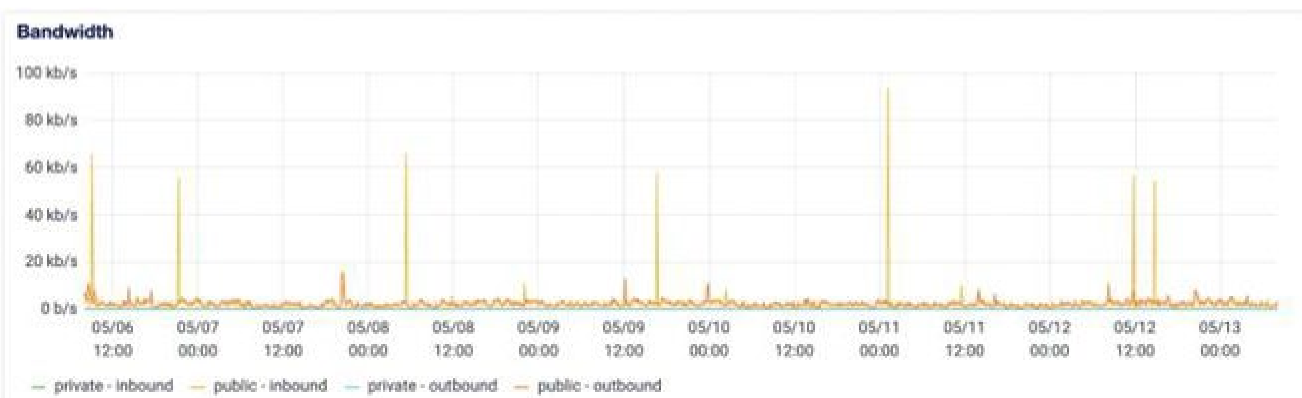


Figure 7. Digital Ocean server bandwidth with user activity

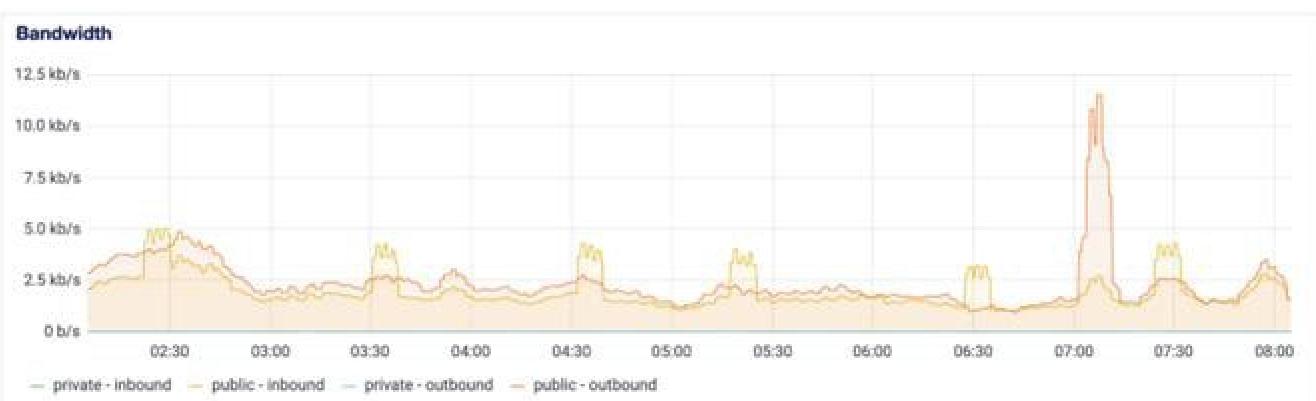


Figure 8. Digital Ocean server bandwidth without user activity

After implementing all the necessary software to maintain OneBusAway, we have identified some possible improvements. Currently, a user interacts with the OneBusAway mobile application, this interaction is recorded in the OneBusAway databases. However, this server interaction does not reach the Mayagüez OneBusAway service. The data on user interaction and accessibility through OneBusAway is available mostly to the maintainers of the OneBusAway program. The data initially obtained by OneBusAway Mayagüez is limited to the generated predictions and registered trajectory of the buses. As an example, retrieving information to calculate a stop's density based on the number of users entering or leaving the bus is challenging and may be inaccurate.

OneBusAway has experienced several updates over time. The initial version installed and deployed was 1.1.15, which was later updated to version 2.1 due to the discovery of a programming language vulnerability in Java. The upgrade to version 2.1 involved a series of changes for the servers. The initial deployment of OneBusAway was carried out through Java integrations and running a bundled OneBusAway software. The deployment was stable in versions 1.1.15 and 2.1, but the service was disrupted due to the unstable implementation of Transit Clock, which generates all predictions for OneBusAway and covers almost the full capacity of the provided server. Before Transit Clock was contained within Docker, the service experienced an almost weekly program crash rate. Docker was implemented to address unexpected and immediate program crashes, allowing the three services to restart if any requirement was not met. Before the Docker implementation, the servers were not suitable to host any of the software implemented due to increased memory usage, leading to application crashes. This issue was resolved after the successful Docker implementation.

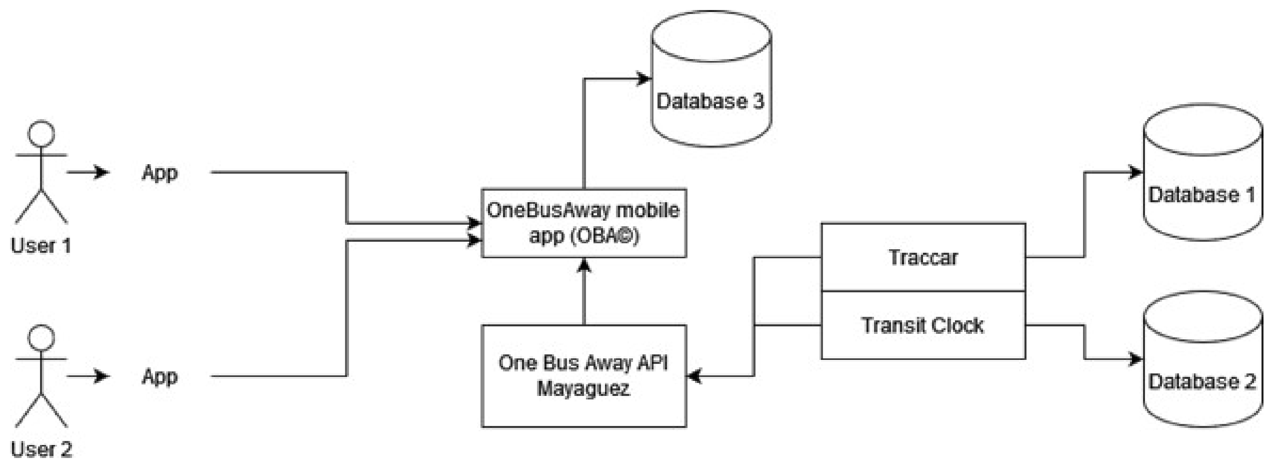


Figure 9. Server structure of One Bus Away Mayagüez

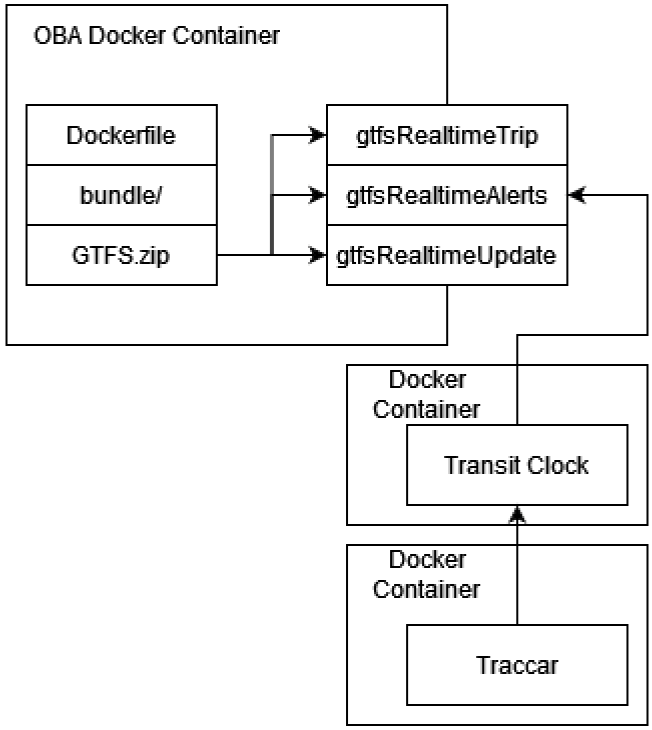


Figure 10. Finalized One Bus Away server state

Chapter 5. Focus Group and User Survey Results

As mentioned in the methodology section, two focus group analyses were performed. The purpose of the first focus group was to study the potential impact of change in travel behavior following the implementation of OBA Mayagüez Beta. The second focus group, which was composed of non-users of public transport, aimed to document travelers' behavior patterns and choice of transportation mode and determine whether the OneBusAway app can influence travel behavior. In addition to the focus groups, data was collected on the travel behavior of the population within the area of influence of the Mayagüez transit system through a survey. The results are shown below.

Focus Groups I

Key highlights from the comments made by the participants include the following:

Origin – Destination (OD)

- For elderly individuals traveling from home to medical appointments
- For the students commuting from home to the university
- For commuting home-to-work

Most of the transit system users were elderly individuals who were captive riders due to factors such as age, no car ownership, or no license.

Conflicts with COVID restrictions

- During the time of this study, due to COVID restrictions limiting the number of passengers to no more than 5 passengers in the vehicle, some of the transit users may not be allowed to board if the bus has the maximum number of passengers on board.

Condition of the stops – Safety

- Many of the participants expressed that the absence of signage and sheltered stops discouraged them from using the transit system. Some said it was due to the lack of knowledge of the system's operation. Some individuals mentioned that the location and lack of safety at the stops made them uncomfortable taking the bus.

Focus Groups II

In the second phase of the focus group, participants were asked about the improvements needed in the transit system to motivate them to use it. Here is a summary of their responses:

- More readily available information
- Due to the lack of signs and information and promotional information, some participants did not have prior knowledge of the transit system's operation.
- Extended operating hours
- Some of the participants expressed concerns that the transit system operates from 6 am to 6 pm, which prevents workers who finish later from using the system to return home.
- Extended routes

There are some highly visited points of interest in Mayagüez that the transit system does not currently reach. The participants expressed their desire to reach these points of interest by utilizing the transit system.

End to the COVID restriction. As the COVID restrictions have caused transit users to miss their trips and waste time waiting for the next bus, ending the restrictions will improve the system's capacity.

In conclusion, the Focus Group provided valuable insights into the potential OBA on traveler behavior.

Survey Results

The survey, conducted from April 2022 to September 2022, included participants of various ages. The age groups with the highest percentage of responses were 18 to 24 at 37.64%, 65 to 85 at 20.30%, 55 to 64 at 12.96%, and 45 to 54 at 12.18%. Participants over 85 years old accounted for the lowest percentage of responses at 1.11%. A total of 337 surveys were completed with data per age per route, with over 50% of participants falling between the ages of 18 and 24. Additionally, a significant percentage of responses by route were collected from participants between the ages of 65 and 85, averaging 16.5% of the respondents. It is noteworthy that only routes 348, 106, and 105 received answers from all age groups between 18 and over 85. Figure 11 shows all the rural routes of the TIM Mayagüez.

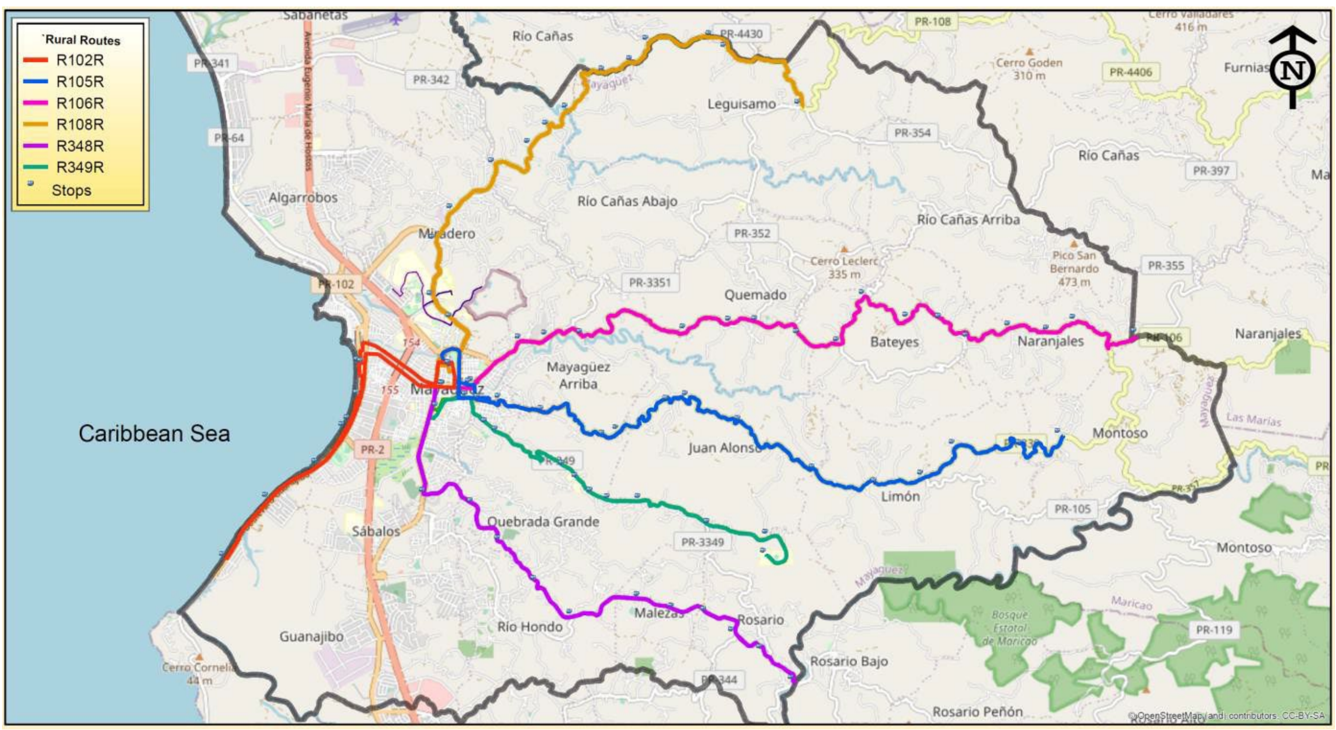


Figure 11. Rural Routes of TIM Mayagüez

The data related to gender shows that 52.59% of the participants were men, 46.67% were women, and 0.74% either chose not to answer or identified as non-binary. When asked if they had any type of disability, 14.81% answered that they had any type of disability, while 84.44% said they did not have any type of disability.

Based on the responses from the participants, 51.15% of the participants reported an annual income of less than $10,000, 17.56% reported incomes between $10,001 and $15,000, 11.07% reported incomes between $20,001 and $40,000, 8.02% reported incomes between $15,001 and $20,000, and 9.17% reported incomes of $40,001 and over $100,000 dollars. Additionally, 3.05% prefer not to answer.

A question about the participants' choice of transportation means was posed, and 172 participants responded, as seen in Figure 12. Notably, on route 349, only 59% of participants reported using private vehicles, while on other routes, over 70% of participants indicated using private vehicles. It should be noted that walking is another frequently used mode of transportation, with route 348 having the highest percentage of participants choosing to walk at 36%, while other routes ranged between 7% and 20%. Carpooling and bicycle use had the lowest percentage of responses, ranging from 2% to 5% on routes 349, 108, and 102. Additionally, participants from all four routes who opted for public transportation (showed in Figure 12 as public car) had an average response of 5%.

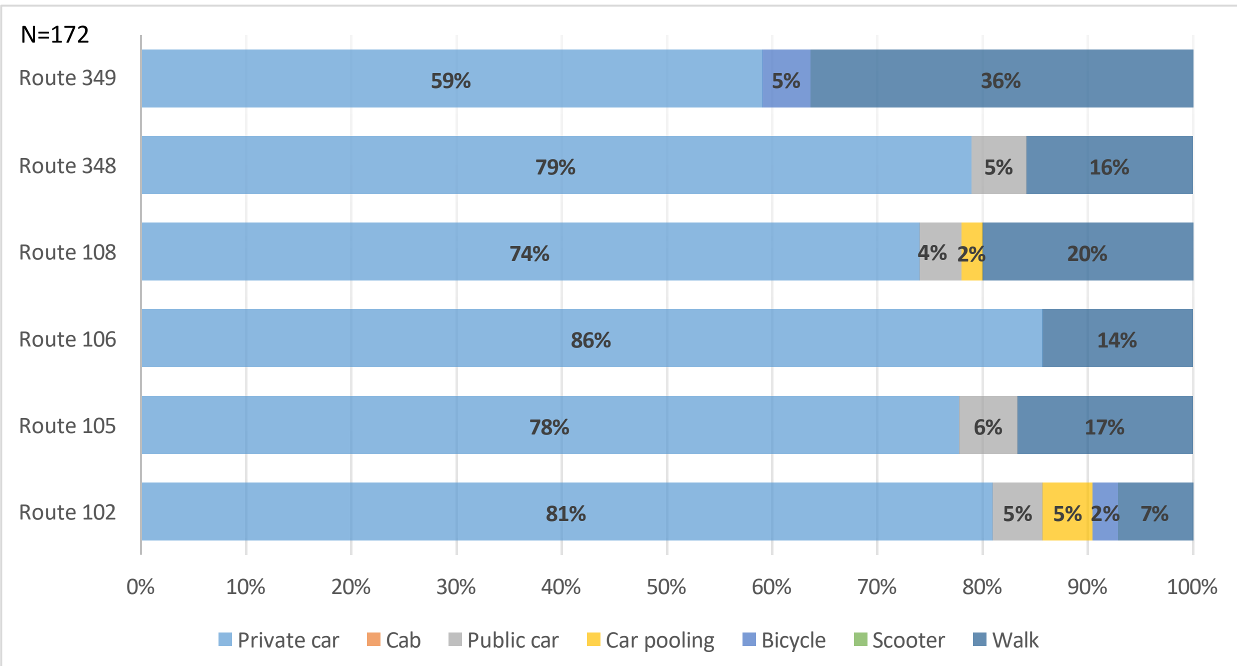


Figure 12. Q11. What means of transport do you use?

Related to the question about the number of people living in participants' homes, out of the 324 participants, 50% of those on route 349 indicated that they lived alone, while on routes 348, 108, 106, 102, and 105, less than 40% of participants reported living alone. Route 102 had the highest percentage (41%) of participants stating they live with at least one other person, while the other routes ranged between 14% and 30%. Concerning households with three or more people, routes 348, 105, and 106 had percentages of 44%, 44%, and 45%, respectively, while routes 349, 108, and 102 registered less than 35%.

Figure 13 show the responses to the question about the number of vehicles owned by participants (car ownership). The results show that at least 10% of participants on every route did not own a private vehicle. Regarding ownership of one vehicle, routes 349, 106, and 102 had the highest percentages, with 57%, 44%, and 41% of participants indicating ownership of at least one car. The remaining routes had less than 40% each. In terms of owning two vehicles, all routes except route 349 had at least 20% of individuals claiming to have two vehicles. Route 105 notably had 34% of participants who owned more than two cars, in contrast to the other routes where fewer than 30% of participants reported owning more than two vehicles.

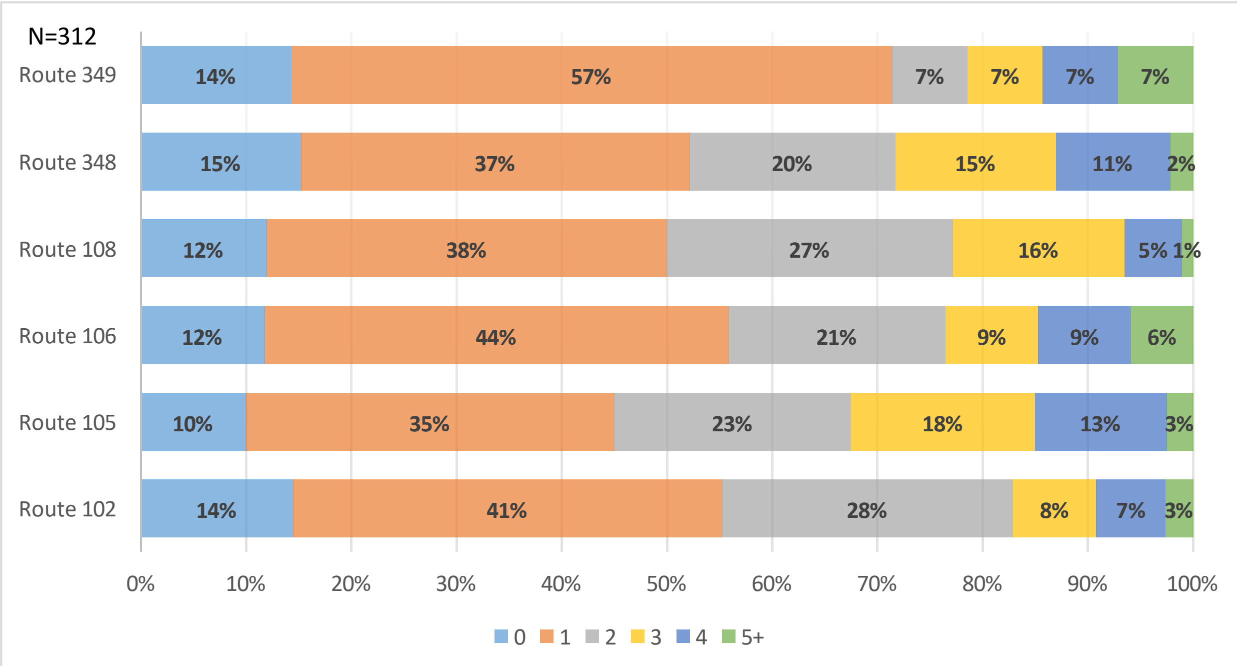


Figure 13. Q13. How many vehicles are in your household?

Unlike other routes, where at least 80% of participants had not used the Mayagüez Integrated Transportation System (TIM), Route 108 had the highest percentage of participants (25%) who reported using the system in the previous year. Question 15 illustrates the use of other transit modes besides the TIM, indicating that at least 10% of participants on every route utilized another mode. Route 348 had the highest percentage (89%) of participants who did not use other modes. Question 15 outlines the means of transit used by participants, with 53% stating "No need" as the primary reason, followed by 11% using taxis and 8% using buses. The use of public transportation via train or public car was reported by 5% of participants, while the use of trolleys stood at 4%, and scooters, carpooling, or walking had the lowest percentage at 2%.

Additionally, based on 79 responses, more than 60% of participants in nearly every route cited "Do not need to use this system" as the main reason for not using the TIM. This was followed by "Does not know the location of the routes" with at least 9% in every route. Only 10% of participants on route 105 mentioned that "the buses do not arrive on time," while on average, 9.33% of respondents cited that "it does not arrive at the usual destination of my trips."

The results of a question about the typical number of trips made by participants in a week show that 8.55% of the respondents make less than two trips per week, while most participants make more than seven trips per week, with 51.97% indicating so. Additionally, 27.63% stated they make at least 4 or 5 trips, and 11.84% reported making between 2 or 3 weekly trips.

The question 27 from the survey is regarding whether participants would leave their private vehicle and use the Mayagüez bus service if they had an application on their cell phone providing real-time information on the location of the buses and predictions of arrivals at the routes. Routes 348, 108, and 102 had the highest percentages of participants (36%, 36%, and 38% respectively) indicating they would be "very likely" to leave their private vehicles if such an application were available. Routes 106 and 105 had over 30% of respondents claiming they would be "somewhat likely" to leave their cars. Across all routes, 31.17% of individuals expressed an indifferent attitude toward using the application. Additionally, less than 15% of participants across all routes indicated that it was "somewhat not probable" that they would use the application.

In the case of the responses concerning safety in using the TIM. Many participants on each route indicated that they felt "very safe" using the system. Only 4% and 6% of respondents on routes 108 and 106, respectively, reported feeling "little safe." While the opinion regarding the customer service provided by bus drivers varied by route. Routes 349 and 348 received the highest percentage of participants claiming that the service was "excellent," while satisfaction on other routes ranged between 46% and 59%. Additionally, only 4% and 6% of participants on routes 108 and 102, respectively, described customer service as "average."

The cleanliness of the buses was assessed on a scale of one to five, with one being the lowest rating. 185 replies were obtained. Most participants rated cleanliness as five in every route except for route 348, where an equal number of participants (35%) gave the route a rating of four or five. It is worth noting that less than 5% of participants rated the cleanliness of the buses as one, which is the lowest rating.

Another aspect evaluated was the satisfaction using the TIM. On all routes shows that more than 60% of participants reported being "very satisfied" with the service, with route 106 demonstrating an even higher percentage of satisfaction at over 80%. Additionally, only 8% of participants on route 106 stated that they were not satisfied with the service provided by the TIM.

Of those surveyed, 17%, 8%, and 18% of participants on routes 108, 105, and 102, respectively, reported using public transportation every day. Routes 349 and 105 had the highest percentages of respondents (43% and 42%) in the “2 to 6 times a week” category. Furthermore, over 60% of individuals on routes 348 and 106 reported using transportation “once a month.” Furthermore, between 13% and 29% of participants on all routes reported using public transportation for at least one year.

With seventy-one (71) responses, a question about the type of activity the participants use transit for was asked in the survey. Routes 348, 105, and 102 are the only routes where participants reported using transit to go to their place of work, with 38%, 18%, and 6%, respectively. Only 6% of the respondents on routes 108 and 102 use transit to go to school. When considering the use of transit to go to the university, routes 349, 348, and 108 have the highest percentages of participants claiming to use it for this purpose, with 29%, 38%, and 44% respectively, while other routes have less than 25%. Additionally, route 102 has the highest number of participants using transit to go to medical appointments, with 53%, whereas all other routes have less than 40%. For recreational and shopping purposes, on average, 17.5% and 11.33% of participants use public transit, respectively.

With seventy-four (74) responses, a question concerning the main reason the participants use transit was asked in the survey and shown that in routes 106, 105, and 102, the most common response, with the highest percentage, was "only transport available" at 46%, 55%, and 50%, respectively. Similarly, in route 348, the same percentage (43%) of respondents selected "save money" and "only transportation available" as their answers. Route 108 had an equal number of participants (35%) selecting "save travel time" and "only transportation available". On route 349, 29% of participants selected "save travel time", "save money", and "only transportation available" in the same proportion.

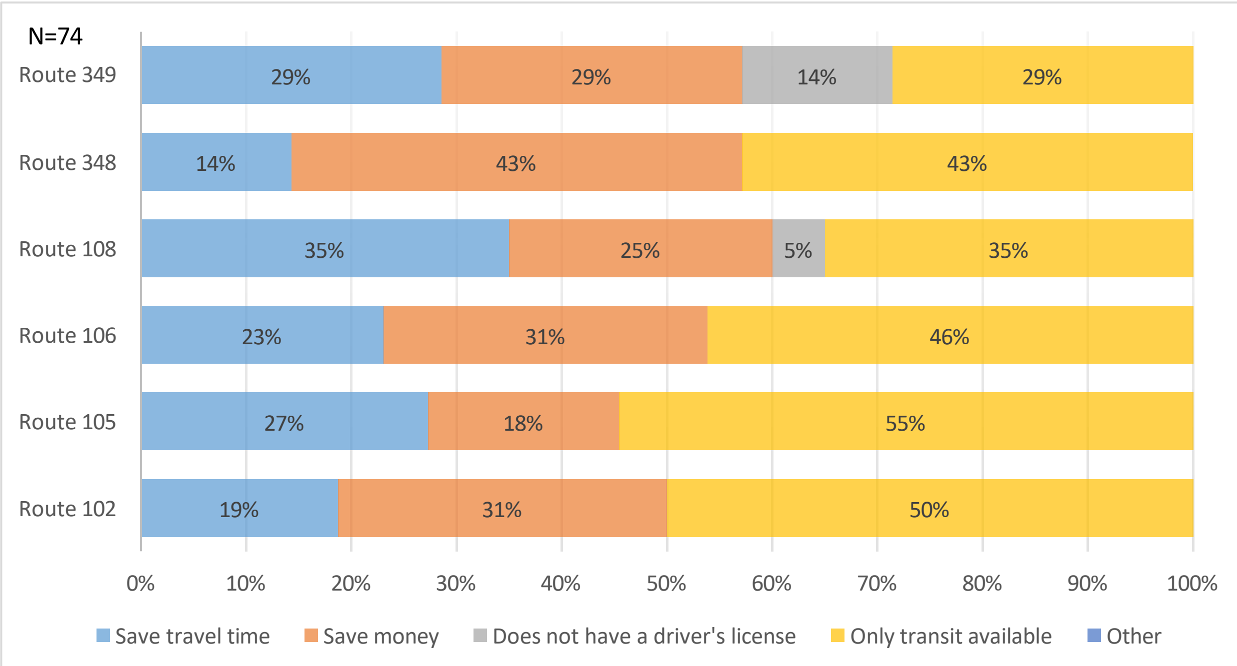


Figure 14. Q27. What is the main reason you use transit?

The participants were asked to rate the conditions of the closest bus stop to their residence from 0 to 10, with 0 not at all adequate and 10 being very adequate. The bus stop receives a rating of "is not at all adequate" from less than 4 % of riders on all routes. Except for route 348, where 15% of the subjects gave the bus stop a rating of 4, with 10 being the highest, less than 10% of participants on each route provided rates from 1 to 4. From 5 to 9, the range of these ratings was between 4 to 26 %. In all routes, more than 20 % of the subjects rated the bus stop as 10, which means that the stop is “very adequate”.

As can be seen in Table 2. , the mean of responses for all the routes was seven (7) points out of ten (10), which can be considered that the bus stop is “somewhat adequate” for most of the subjects. The table also shows that the standard deviation in all routes is almost the same, which is the one that measures the dispersion of the distribution of the data and is between 2.327 and 2.959. As it was said in the previous paragraph, the highest rate was ten (10) in all the routes, and the lowest was 0 in routes 108, 348, 349, one (1) in routes 105 and 106, and two (2) in route 102.

The aspects that participants considered relevant at a bus stop were asked, with ratings from 1 (least important) to 4 (most important). Security was identified as the most important aspect, receiving a rating of 4 from 58% of the participants. Walking Access was considered somewhat important, with 37% of the participants giving it a score of 3. Information was ranked somewhat less important, with 34% of participants assigning it a rating of 2. Amenities were considered the least important aspect, with 30% of participants giving it a rating of 1.

The participants were asked to rank pedestrian access aspects, information aspects for pedestrians, various amenities of the bus stops, and safety-related factors from least important to most important. In the case of pedestrian access aspects, including the sidewalk, platform for bus access, and disabilities access ramp, the rank was from least important (1) to most important (3). The sidewalk was considered the most important aspect by the participants, with 63% of them giving it a score of 3. The disabilities access ramp was also deemed important, with 57% of participants awarding it a score of 3. Conversely, the platform for bus access was considered the least crucial factor, receiving a score of 1 from 39% of the participants.

Table 2. Q40. What score would you give to the stop, from 0 to 10, where 0 is a stop that is not at all adequate and 10 is a stop that is very adequate?

Route	N	Mean	SE Mean	StDev	Minimum	Median	Maximum
102	55	7.24	0.333	2.472	2	8	10
105	23	7.39	0.532	2.554	1	8	10
106	81	7.25	0.259	2.327	1	8	10
108	61	6.98	0.338	2.643	0	7	10
348	28	7.25	0.534	2.824	0	8	10
349	30	7.00	0.54	2.959	0	8	10

In the case of information aspects for pedestrians, including "Stop sign with number", "Information printed on the stop or screen that shows the information", and "Cell application that gives real-time information on the location of the buses," the ranking was from most important (3) to least important (1). The most relevant aspect considered related to pedestrian information was "Stop sign with number," with a score of 3 assigned by 63% of the subjects. "Information printed on the stop or screen that shows the information" was considered somewhat important, with 40% of participants assigning a rating of 2. The least important aspect was the "cell application that gives real-time information on the location of the buses," with 37% of the subjects giving it a value of 1.

In the case of various amenities, including shelter, bank, bicycle carrier, vending machine, and trash can, the ranking was from the most important (5) to the least important (1). "Vending Machines" was considered the least important aspect, with over 50% of the subjects giving it a score of 1. "Bicycle carrier" was rated as somewhat unimportant by 40% of the participants, who gave it a score of 2. "Trash can" was considered an important element, with 41% of the subjects rating it as 3. "Bank" was rated as somewhat important with a score of 4 by 34% of the respondents. Finally, "shelter" was identified as the most important factor, with 52% of participants rating it as 5. Regarding safety-related factors, the ranking was from most important (3) to least important (1). The results indicate that more than 50% of participants assigned each safety-related factor a score of 3, except for cleanliness, which received the next highest score. This suggests that most participants considered the characteristics to be equally significant.

Respondents were asked to assign scores to stops. Scores given to bus stops on all routes range from 0 to 10, with 0 representing a stop that is not at all adequate and 10 indicating a stop that is very adequate. Routes 102, 348, and 348 received the highest percentages of respondents rating a stop as very adequate, with 34%, 34%, and 41% respectively giving a score of 10. For scores between 5 and 9, the percentages ranged from 24% to 3% for all stops on the route, while the percentage for scores between 4 and 0 ranged from 2% to 14%. The overall mean rating for the survey was 7 out of 10, as shown in Table 5, indicating that bus stops were rated as somewhat adequate by most respondents. The table also presents the maximum, minimum and median scores given by participants for each route, with the standard deviation, which indicates the dispersion of the data distribution, which varies between 2.467 and 3.07.

The participants were asked about the use of smartphones among the subjects. Results show that more than 50% of the respondents in all routes claimed to have a "very good" understanding of smartphone use. On average, 16.33% of the participants were considered to have a "good" knowledge, while the percentage of individuals considered to have an "average" knowledge of smartphone use ranged from 2% to 16%. The percentage of individuals who were thought to have "not much" understanding of smartphone use ranged from 3% to 19%. Additionally, regarding the use of the smartphone "only for calls," less than 15% of the respondents in all the routes indicated this.

In relation to usefulness for having real-time bus arrival predictions, the responses across all routes indicate a high level of usefulness for having live-time bus arrival predictions, with percentages ranging from 61% to 86% of respondents finding this feature very useful for trip planning. While concerning how often the surveyed participants use mobile applications such as Maps, Google Maps, and Waze for their trips, 32.05% of participants use such applications once a year, while 19.23% use them daily.

Chapter 6. Ridership Data Results

Annual and Average Boarding

Figure 15 provides a summary of the annual boarding data from 2019 for the TIM routes. Routes 106 and 348 stood out with the largest number of annual boardings, with over 31,000 individuals using the system in 2019. Routes 102, 105, and 108 had between 24,000 and 30,000 annual boardings, while route 349 had the lowest at 1,484 in three months (This was a new route that initiated operations in the middle of October 2019). In Table 3, the total number of boardings for the system in 2019 is reported as 148,794 passengers. Route 349 had the lowest boardings that year with an average of just 592 people per month, while most other routes had monthly averages ranging between 2,000 and 3,000 passengers. However, Route 349 was a newly implemented route that year; therefore, its ridership was picking up during the two and a half months after starting operations. For all routes, the daily average ranged from 28 to 133.

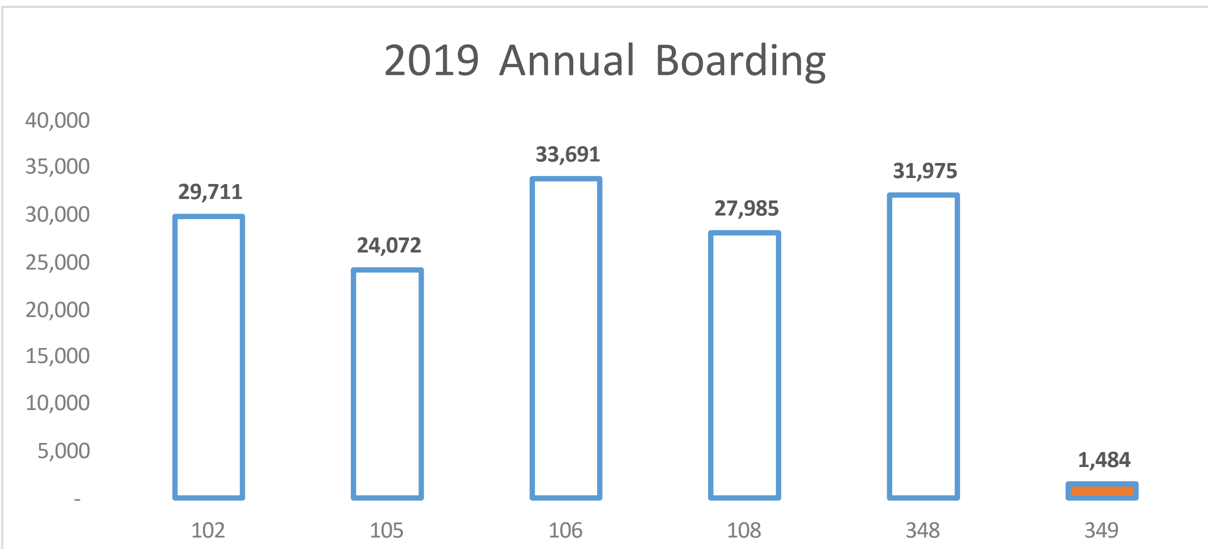


Figure 15. Annual Boarding

Table 3. Average Boarding

Route	**Total** Boardings	Monthly Average	Daily Average
102	29,663	2,472	117
105	24,060	2,005	95
106	33,691	2,808	133
108	27,948	2,329	110
348	31,953	2,663	126
349	1,479	592	28
All Routes	**148,794**	**12,868**	**608**

Routes Boarding

All the routes have data of the annual total boardings per stop and direction. Figure 16 16 shows route 102, as it starts its journey in "Terminal Barcelona" which is the main terminal for public cars, Sultana (a private bus company that makes trips from Mayagüez to San Juan every day), and the TIM. PR-102 is the road along this route, also called "Boulevard Guanajibo" and its last stop before going to the terminal is "Plaza Colon", this route has eleven stops including the terminal. It is worth mentioning that at the "Ramirez Arellano" stop, passengers can only board when the bus is returning to the station. As can be observed in Figure 16, Terminal Barcelona had the highest amount of boardings with 8,560 passengers. The stops "Parque Skateboard" and "Res. Candeleria" are the second and third stops with a large amount of boarding with 5,373 and 4,788, respectively. The stops "Villa Pesquera" and "Connector Nenadich" had fourth and fifth most boardings with 2,832 and 2,126 passengers. The other five stops left had less than 1,500 boardings per stop.

Figure 17 shows the annual transit boarding numbers for various stops along rural route R105R. This graph shows a variability in boarding numbers across the stops. The Terminal has the highest boarding figure at 7,984, highlighting it as a major center of activities for commuters. Cancha Rolón also stands out with 1,845 boardings, suggesting significant commuter activity. In contrast, other stops like Calle Cantera inbound and Calle Cantera outbound report much lower boarding numbers, with 112 and 58 boardings respectively, which could indicate lower demand or accessibility issues at these locations.

Figure 18 shows the boarding of route 106. The data shows substantial variability in ridership, with certain stops demonstrating much higher boarding numbers. Notably, the Terminal Balboa Outbound and the Terminal exhibit the highest ridership, with 8,892 and 7,478 boardings respectively, underlining their importance as major transit nodes. Other stops such as Int. Carr 352 inbound and Escuela El Consumo also have significant boardings, with 2,070 and 1,934 respectively. These values could indicate areas of high commuter engagement. Instead, stops like KM 9.5 Sector Villa Los Robles and Int. 354 outbound have much lower boarding figures, at 51 and 67 respectively, suggesting either less strategic locations of the stop, or lower demand.

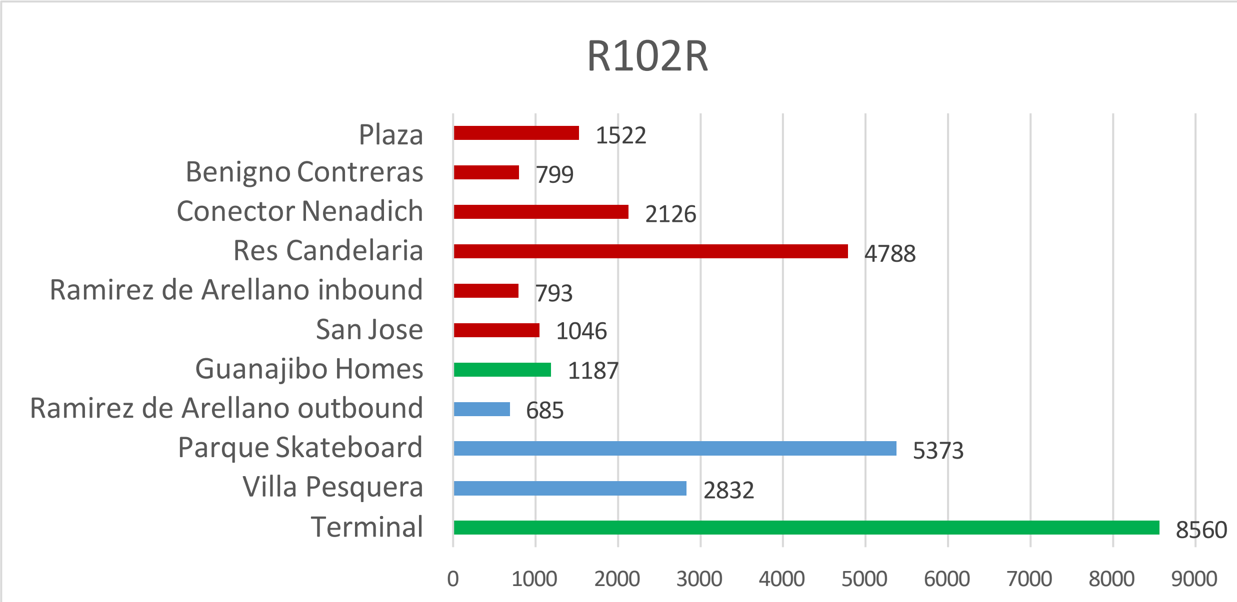


Figure 16. 2019 Boarding Data of Rural Route 102

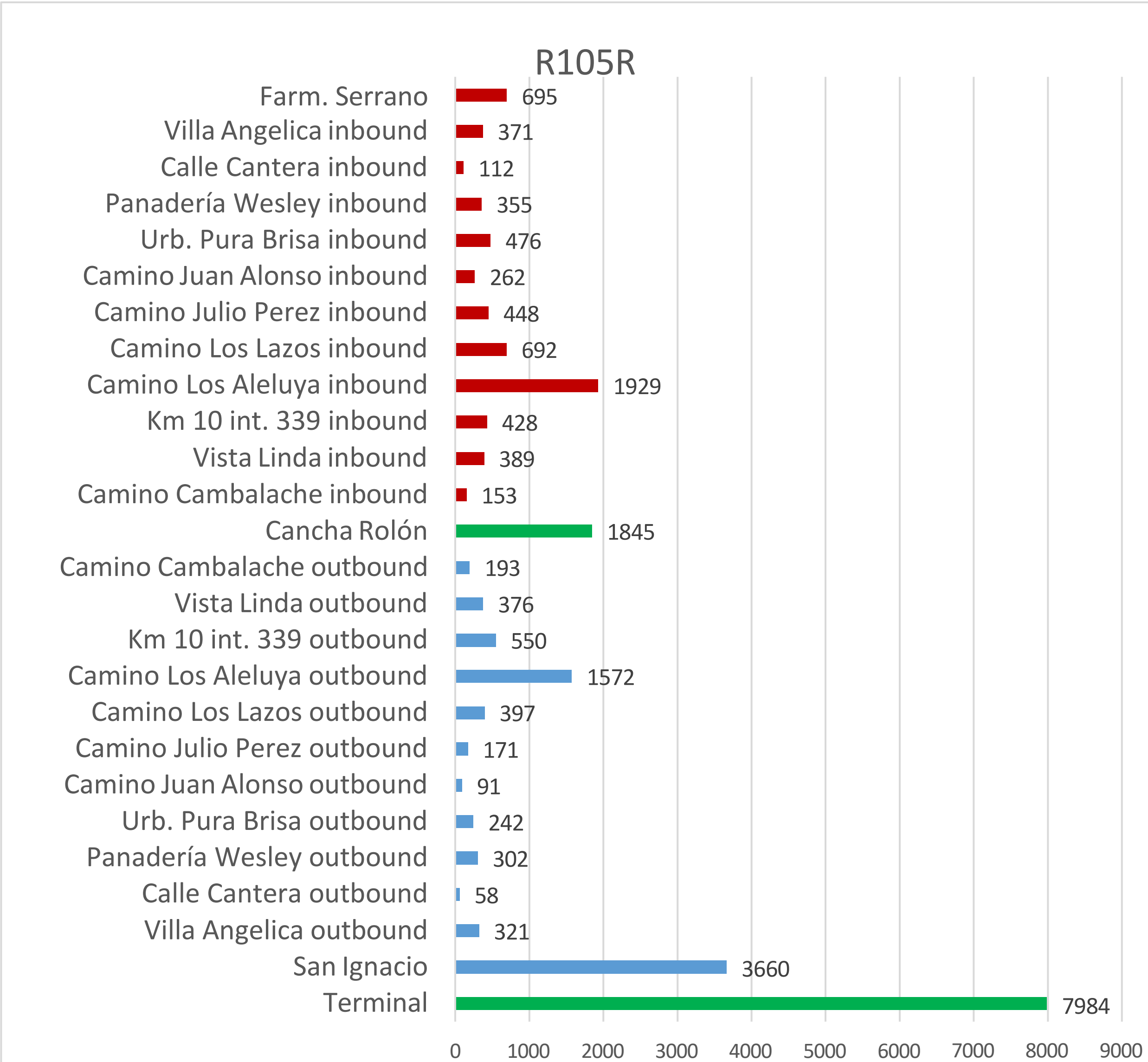


Figure 17. 2019 Boarding Data of Rural Route 105

Figure 19 illustrates passenger boarding along rural route R108R. The Terminal dominates the chart with the highest number of boardings at 12,840, highlighting its central role in the network. Similarly, Sector Botoyo inbound also records high ridership with 2,084 boardings, indicating a significant demand in this area. Other notable stops include INT. Carr. 342 inbound and Conde. El Pabellon inbound, with substantial boarding numbers at 913 and 875, respectively, reflecting their importance in the network. In contrast, several stops like Urb. El Retiro outbound, Km 5.4 Miradero Gardens outbound, and Camino Meliton Rivera outbound have relatively low boarding numbers, with 110, 58, and 756 respectively. These figures might suggest lower utilization, potentially due to less optimal locations or insufficient connectivity.

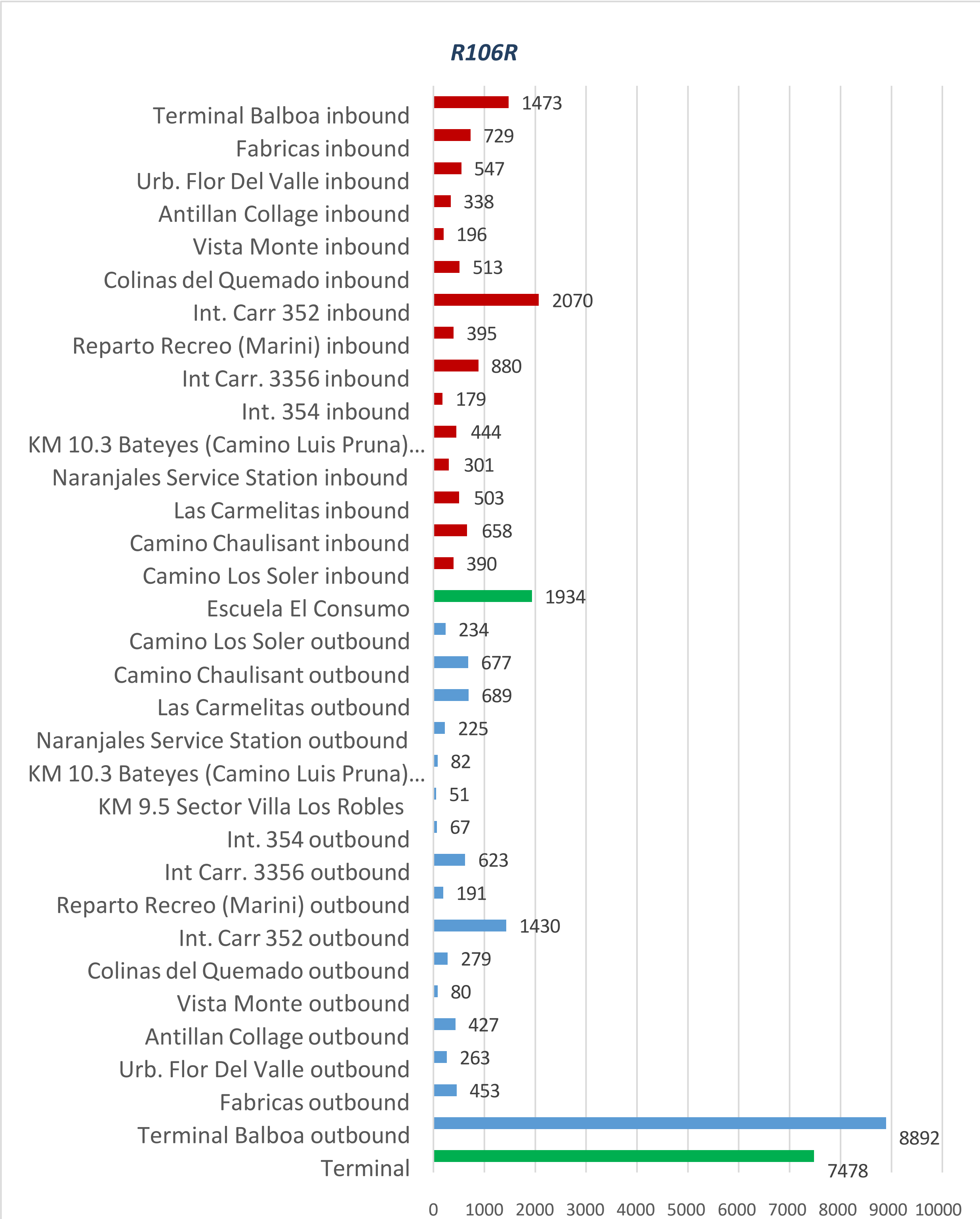


Figure 18. 2019 Boarding Data of Rural Route 106

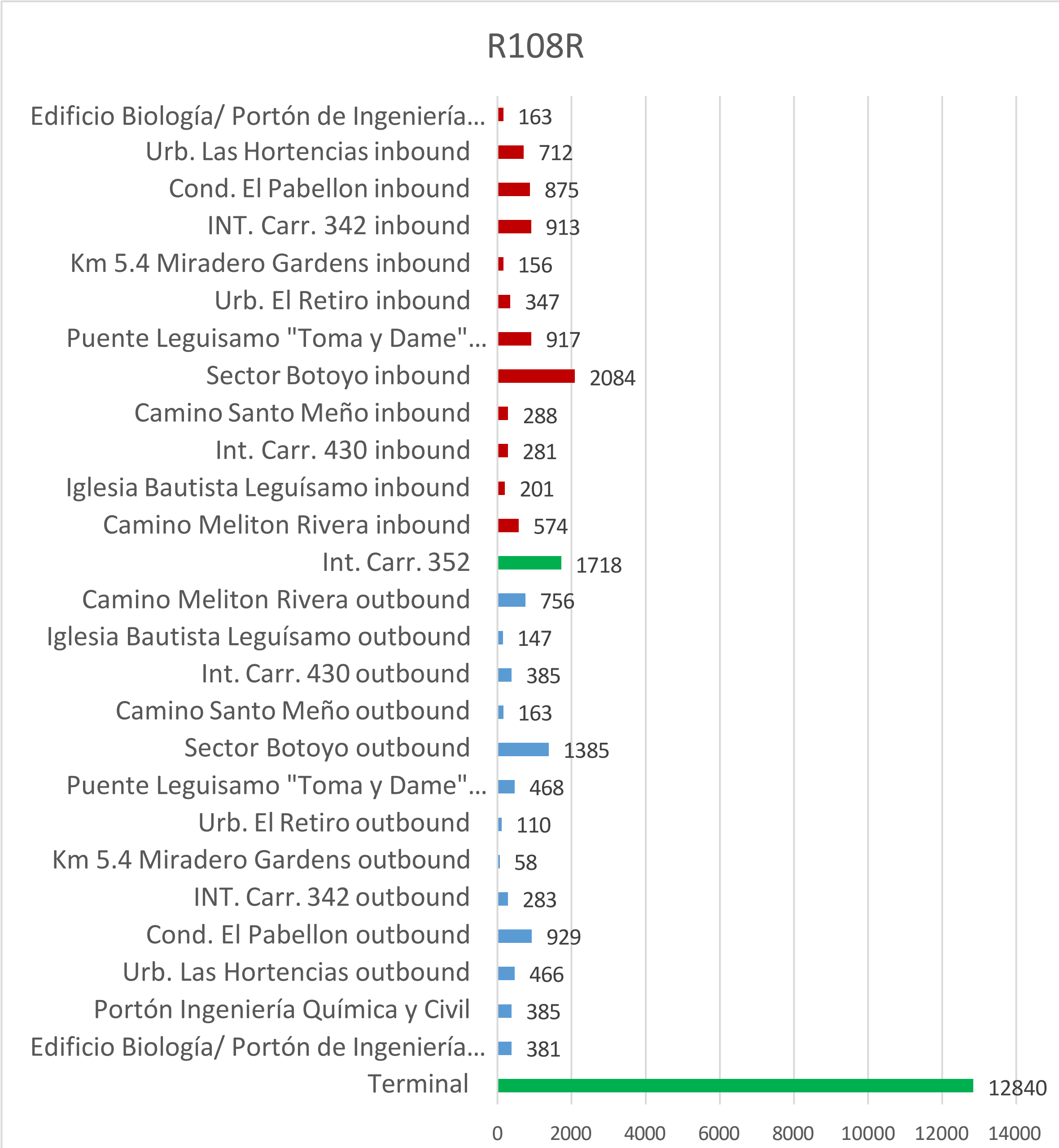


Figure 19. 2019 Boarding Data of Rural Route 108

Figure 20 provides a detailed overview of the annual boarding numbers at various stops along rural route R348R, showing the variations in rider engagement. The Terminal has the highest boarding number at 10,311, underscoring its central importance in the route network. Plaza also shows substantial usage with 2,665 boardings, indicating it as another key stop within the route. Other stops like Cuesta Las Piedras inbound and Galleria La Candelaria inbound also see considerable boardings, with 1,739 and 1,532 respectively, highlighting their roles as significant transit locations. On the lower end, stops such as Cruz Monte Km 7.2 inbound and Villas del Rosario inbound have much fewer boardings, at 258 and 244 respectively, which might indicate lower demand or accessibility issues at these stops.

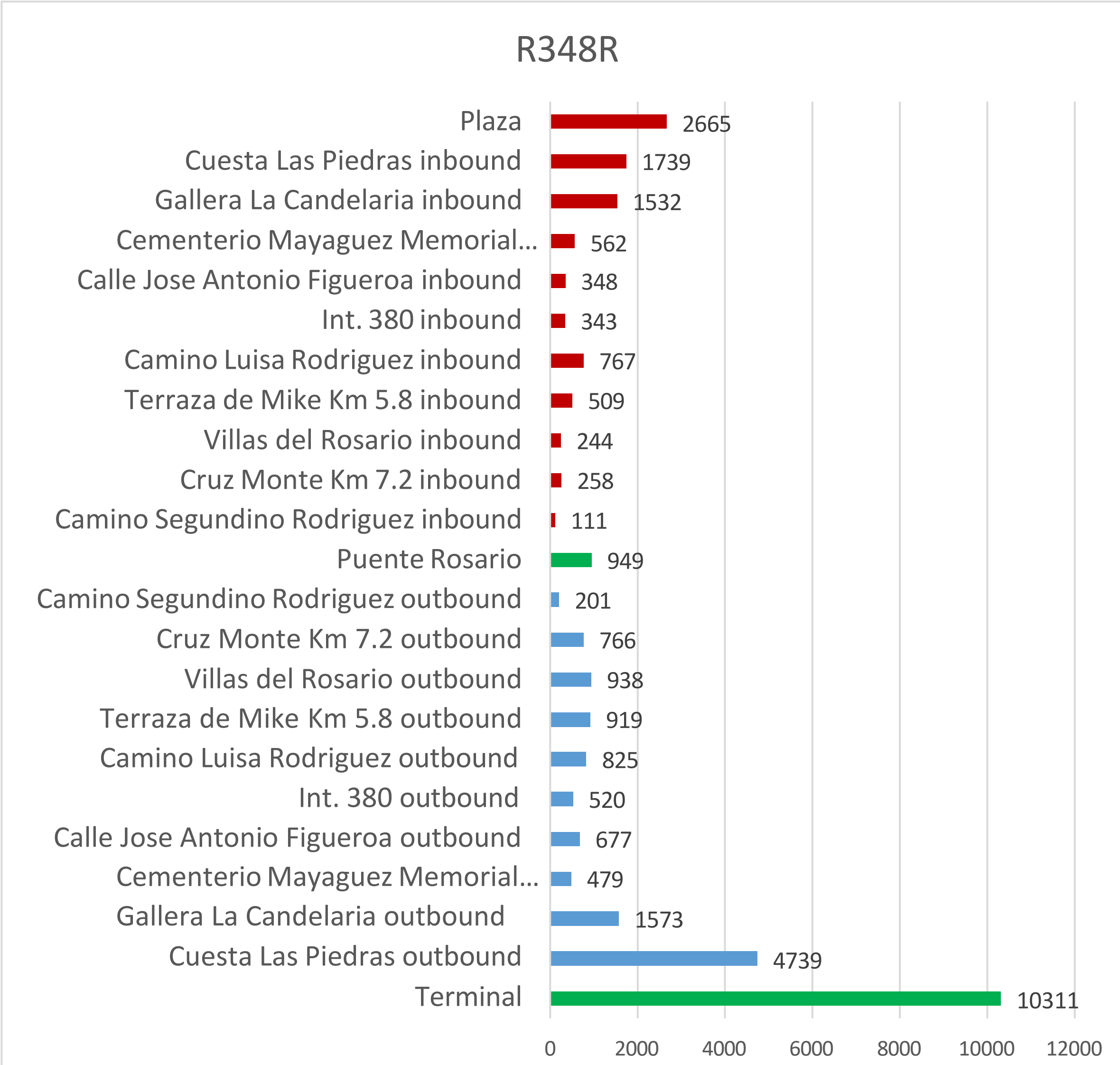


Figure 20. 2019 Boarding Data of Rural Route 348

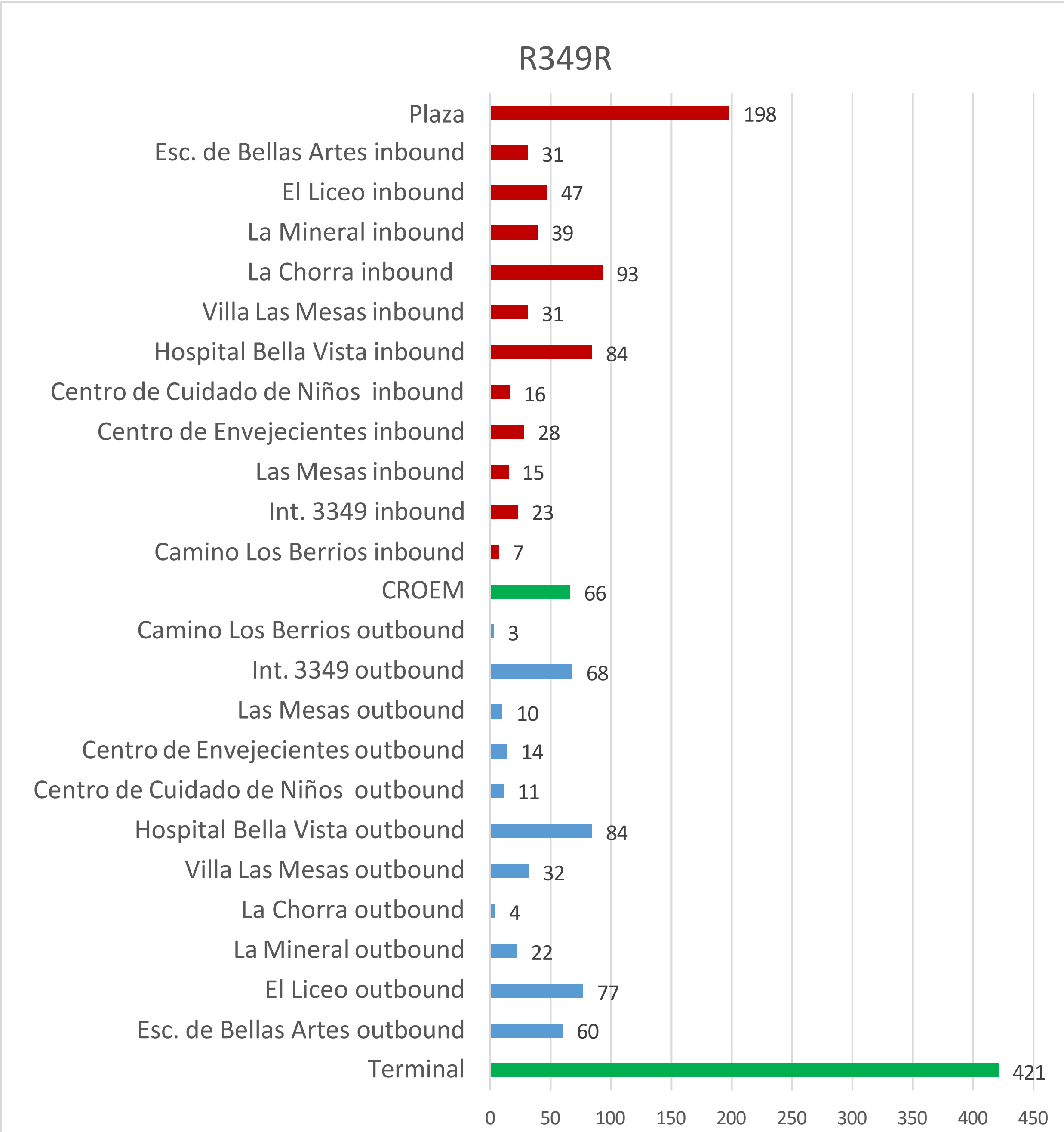


Figure 21. 2019 Boarding Data of Rural Route 349

Figure 21 shows the annual boarding along rural route R349R, revealing a distinct pattern in ridership. The Terminal leads with the highest boarding count at 421, making it a crucial node for commuter traffic on this route. Plaza also shows considerable activity with 198 boardings, serving as a significant transit point. Other locations like La Chorra inbound and Hospital Bella Vista inbound have moderate boarding numbers at 93 and 84 respectively, suggesting a steady flow of passengers. However, many stops, including Centro de Cuidado de Niños inbound, Las Mesas inbound, and Camino Los Berrios inbound, exhibit very low boarding numbers, all below 25, which might reflect lower demand or accessibility challenges at these stops.

Chapter 7. Modeling Characterization of the Demand and Activity System

Lineal correlation results

Figure 22 shows a correlation matrix with scatter plots and distribution plots for several variables related to demographic and transportation data. The variables analyzed as were mentioned in the section *Census Data*, are the following:

- Abordaje (Boarding). The number of passengers who board a bus at a stop in a certain area. This area includes one or more stops corresponding to one or more routes.
- AreaTransbord (Transfer). Indicates whether there are multiple bus stops in the studied area.
- Pop. The population size in the studied area. This variable represents the total number of residents within a specific geographic region.
- MedAge. The median age of the people living in the studied area.
- HouseHold. The number of households in the studied area. This variable indicates the total number of residential units or family living within the area.
- MHHoldInc. The median income of households in the studied area. This variable provides information about the economic status of the residents.
- VehOwnersh (Vehicle Ownership). The number of owned or rented vehicles within the study area.
- VehperHH. The average number of vehicles per household in the study area.
- X.HHwCell. The average number of cell phones in households in the studied areas.
- X.HHnoInter. The average number of Households without internet in the study area.
- X.HHmore60. The average number of people aged 60 or over in households in the studied areas.

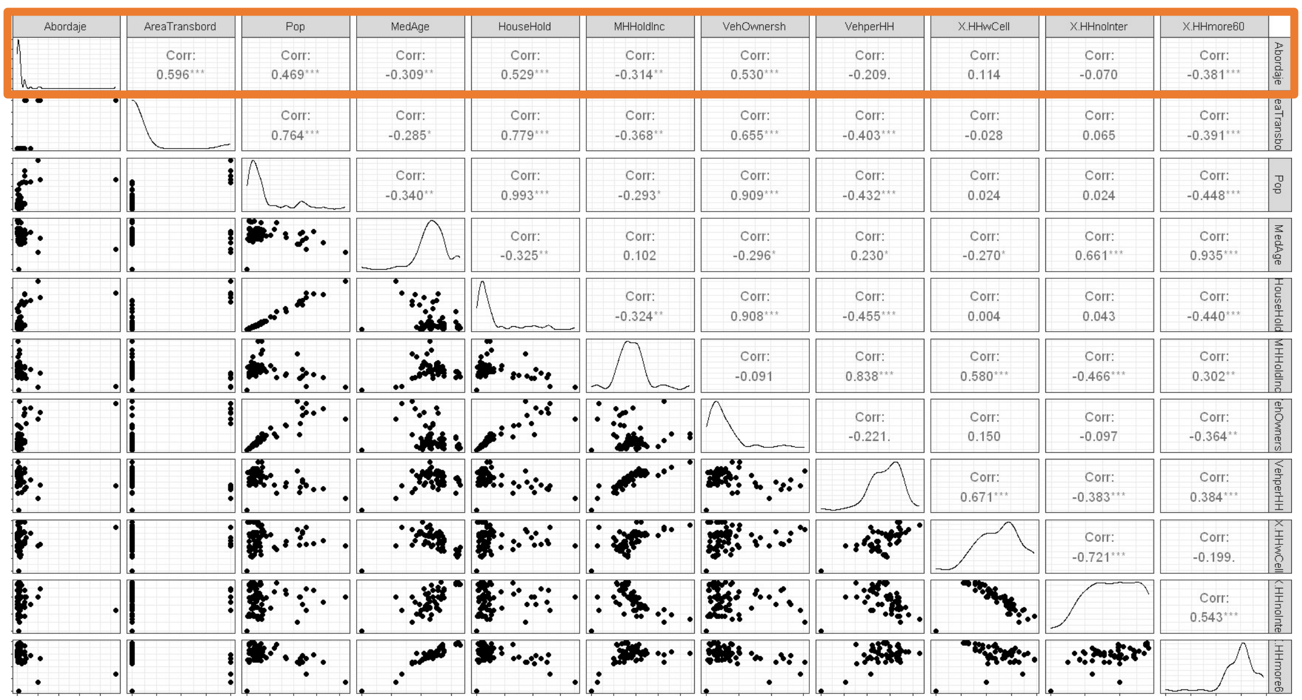
The correlations of these variables highlight the relationships between them, like population density, household characteristics, and transportation infrastructure. Generally, areas with higher populations and more households tend to have more transportation options, higher vehicle ownership, and different age demographics. These factors interplay to define the socio-economic and infrastructural characteristics of the studied area.

A look at the correlation matrix shows us, first, that the population size is positively correlated with the number of households (0.779***). This is expected, as areas with more people will naturally have more households. A higher population often translates to more households because as the population increases, the demand for housing also rises, leading to more households being formed to accommodate the growing number of residents. Similarly, the number of households strongly correlates with vehicle ownership (0.909***). More households typically mean more vehicles are owned, as each household is likely to own at least one vehicle. This strong correlation indicates that vehicle ownership scales with the number of households. Population size is also positively correlated with vehicle ownership (0.655***), as more people in an area tends to result in a higher number of vehicles. Additionally, the number of owned or rented vehicles correlates highly with the average number of vehicles per household (0.838***). This correlation is expected since more vehicles in an area leads to a higher average per household.

Population size positively correlates with the presence of multiple stops in an area (Corr: 0.764***), indicating that more populated areas are likely to have more transportation infrastructure. Larger populations necessitate more extensive public transport systems to meet mobility needs. Areas with more people tend to have more bus stops, train stations, and other transit points. Similarly, the number of households correlates with the presence of multiple stops (0.779***), reflecting the need for more transportation options in densely populated residential areas.

There is a strong correlation between the number of households and the number of people aged 60 or over in households (0.935***). This suggests that areas with more households have a higher proportion of older residents. The median age negatively correlates with the population size (-0.340**). Younger populations are often more common in highly populated areas due to factors such as urbanization and the availability of employment opportunities. Urban areas typically offer more job opportunities, educational institutions, and various amenities, attracting younger individuals and often resulting in higher population densities in these regions. Similarly, the median age negatively correlates with the number of households (-0.340**). Areas with more households might have younger populations, reflecting family formations and younger demographics.

Emphasizing the correlation between the variable "Boarding" and the other variables provides a comprehensive view of how different demographic and socioeconomic factors influence the number of passengers boarding the bus. The significant positive correlation between the number of boardings and the presence of multiple stops in an area (Corr: 0.596***) suggests that areas with more bus stops tend to have a higher number of boardings. This is because greater accessibility and availability of stops facilitate the use of public transportation.



Legend: Sig: '*' 0.001; '**' 0.01; '*' 0.05 '; .' 0.1 '**

Figure 22. Lineal Correlation Matrix

The population also shows a significant positive correlation with the number of boardings (Corr: 0.469***), indicating that areas with higher population density result in greater use of public transportation. This relationship makes sense, as a larger population increases the demand for transportation due to residents' mobility needs. On the other hand, the average age of residents shows a significant negative correlation with the number of boardings (Corr: -0.309**). Areas with a higher average age tend to have fewer boardings, possibly because older individuals might depend less on public transportation due to reduced mobility or a preference for other modes of transportation. The number of households in an area also has a significant positive correlation with the number of boardings (Corr: 0.529***). Areas with more households tend to have a higher number of boardings, which is expected since more households means more people who might use public transportation.

Median household income shows a significant negative correlation with the number of boardings (Corr: -0.314**). Areas with higher median incomes tend to have fewer boardings, suggesting that wealthier families might prefer using private vehicles over public transportation.

Vehicle ownership also shows a significant positive correlation with the number of boardings (Corr: 0.530***). This indicates that even in areas with high vehicle ownership, public transportation remains a viable option. People might use public transportation to avoid parking issues or for certain types of trips where public transportation is more convenient. The positive correlation also means that households that own one vehicle might be used by one person and might still have other habitants that need and use transit for their needs. This last explanation is also supported by the negative correlation between the average number of vehicles per household and the number of boardings (Corr: -0.209) is not significant, but it suggests that more vehicles available per household reduces the need to use buses. Therefore, less vehicles available per household might generate transit trips.

The average number of cell phones per household shows a weak positive correlation with the number of boardings (Corr: 0.114), although it is not significant. This finding might be anecdotal or reflect other underlying factors not directly related to cell phone ownership. However, this weak correlation also means that no transit information was provided by cellphone at the time of the survey. Therefore, there is an opportunity to provide information that might be able to strength the correlation of cellphone uses with boardings. The weak negative correlation between the average hours without internet in households and the number of boardings (Corr: -0.070) is also not significant. Areas with poorer internet connectivity might have socioeconomic factors that affect public transportation use.

Finally, the significant negative correlation between the average number of people over 60 years old in households and the number of boardings (Corr: -0.381***) suggests that areas with older individuals tend to have fewer boardings. Older individuals might have different mobility patterns and depend less on public transportation. This is an interesting and counterintuitive finding because previous studies performed by the research team in phase one of this project found that more than 50% of passangers using the TIM system were over 60 years.

Spatial correlation results

As mentioned in Methodology, Moran's Index, ***I***, is a measure of spatial autocorrelation that evaluates whether the spatial distribution of a variable is clustered, dispersed, or random. The value of Moran's ***I*** range from -1 to +1: a value of +1 indicates perfect positive spatial correlation (clustering), 0 indicates no spatial correlation (random distribution) and a value of -1 indicates perfect negative spatial correlation (dispersion).

The results of the Boarding variable analysis in the bus stop areas and the neighboring of each stop results in a coefficient of 0.1316. This Result of the Moran's ***I*** value indicates a weak positive spatial correlation, suggesting a slight tendency for high boarding values (stops with many boardings) to be near other high values and low values to be near other low values. This means that a high boarding at the neighboring bus stop is related to the boarding at the reference stop. However, this clustering is weak, indicating that either there is no spatial correlation, or the spatial correlation is due to other factors that were not considered and that could be found in a spatial regression analysis. Despite this, some clustering of boarding activity exists, which might indicate that certain areas with bus stops have slightly higher boarding numbers due to specific factors such as proximity to residential areas, or commercial centers. Therefore, while some areas might show a concentration of boardings, the overall pattern is relatively random.

Several factors could explain the weak positive spatial correlation observed. The spatial distribution of bus stops and their connectivity to other transportation modes or destinations are influential. Demographic and socioeconomic factors also play a role, as areas with higher population densities, more households, or specific demographic characteristics might see more boardings, albeit weakly grouped. Additionally, the frequency of bus service and the design of routes can impact how passengers distribute themselves across different stops. Lastly, the condition of stops regarding shelter and security, the accessibility of stops, and their proximity to important amenities, such as shopping centers, schools, and hospitals, might contribute to the weak clustering effect observed.

Spatial modeling results

Table 4 presents spatial regression analysis results using a negative binomial probability distribution, with the number of passengers boarding at bus stops (Boarding = Abordaje) as the dependent variable, and various demographic and transportation variables, as the independent variables. The Moran's ***I*** coefficient for the regression is 0.3043 with a p-value of 0.00317, which indicates a significant spatial correlation in the residuals, however, the most significant model variables were not those related to the spatial analysis such as variable *lagx*. Pop with a significance of 0.1 and lagx.HouseHold which turned out to be not significant. This indicates that although the model serves to predict boarding considering neighboring variables, the *lagx.* Household variables alone do not explain part of the passenger behavior related to boarding.

The spatial regression analysis reveals that the number of stops in the area, vehicle ownership, and the presence of multiple stops positively influence public transport usage. Conversely, higher average age and median household income negatively impact boardings.

Table 4. Spatial regression analysis results

Coefficients:	Estimate	Std.Error	z value	p-value	Sig.
(Intercept)	5.85439939	0.75534158	7.751	9.15E-15	***
AreaTransb	1.07181262	0.55526335	1.93	0.05357	.
MedAge	-0.03954981	0.01982783	-1.995	0.04608	*
MHHoldInc	-0.00006942	0.00002777	-2.499	0.01244	*
X.HHnoInter	2.48156923	1.53773734	1.614	0.10658	
VehOwnersh	0.00288424	0.00102894	2.803	0.00506	**
VehperHH	1.85671334	0.62271966	2.982	0.00287	**
lagx.Pop	0.00438302	0.00264273	1.659	0.09721	.
lagx.Household	-0.01109561	0.00740282	-1.499	0.13392	

Legend: Sig: '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '**

The presence of multiple stops in the area (AreaTransbord) positively affects boardings, with an estimate of 1.07181262 and a p-value of 0.05357. Areas with multiple bus stops have more boardings, which is expected as increased availability and accessibility encourage more people to use public transport. The number of owned or rented vehicles (VehOwnersh) positively correlates with the number of boardings, with an estimate of

0.00288424 and a p-value of 0.00506. Similarly, the average number of vehicles per household (VehperHH) also has a significant positive effect on boardings, with an estimate of 1.85671334 and a p-value of 0.00287. This indicates that areas with high vehicle ownership, and with a higher average number of vehicles per household tend to have significantly more boardings. This may seem counterintuitive, but it could suggest that households with more vehicles are in regions where public transport is still a necessary complement for certain trips, perhaps due to parking constraints or traffic congestion.

The average age of people living in the studied area (MedAge) shows a significant negative effect on boardings, with an estimate of -0.03954981 with a p-value of 0.04608. A higher average age in an area is associated with fewer boardings, possibly because older populations might have different mobility needs or preferences, relying more on private transportation or having less frequent travel requirements. Median household income (MHHoldInc) also negatively impacts the number of boardings, with an estimate of - 0.00006942, and a p-value of 0.01244. This suggests that wealthier areas might have residents who are more likely to use private vehicles rather than public transport.

Chapter 8. Strategies to Improve a Transit System and Reduce Traffic Congestion in the Transportation Network

To develop strategies that improve the public transportation system and contribute to reducing traffic congestion in the transportation network, the research team considered the literature review, the results of the focus groups, the comprehensive survey among users and non-users of the transit system, the spatial correlation analyses, and the development of a spatial regression model.

The implementation of isolated strategies can improve certain aspects of the transportation system. However, if we aim to address vehicle congestion effectively and utilize collective transportation as a key element in this strategy, it's essential to implement measures that may be drastic but have the potential to significantly alleviate the congestion problem.

A comprehensive strategy will be presented at the end of this chapter. Initially, this section discusses how the results of various activities conducted in this study have provided indications of the strategies that are necessary to improve the transit system.

According to the survey results, a group of non-users of the public transportation system indicates that they lack knowledge of the location of the routes. Therefore, a comprehensive strategy must include marketing the system.

The transit system that will be promoted needs to be strong, efficient, effective, and reliable. Users consider it crucial that the buses arrive at their stops on time. Between 61% and 86% of users find it extremely useful to have a Real-Time Passenger Information (RTPI) application. This application provides them with predictions of when the buses will arrive at the stops they use. Additionally, survey results for non-users of the public transportation system show that between 30% and 40% agree that an RTPI application such as OneBusAway could encourage them to leave their private vehicles at home and use public transportation. Therefore, a comprehensive strategy must include an RTPI application.

For the public transportation system to be attractive to both current and potential users, it should have very good infrastructure throughout. This includes an adequate location to wait for buses, good sidewalks in the system's area of influence to ensure good accessibility, and a physical structure with shelter and information at the stops that also contributes to the comfort and safety of users at the stops.

Excellent ideas are obtained from the literature review that contributes to generating an integrated strategy for using public transportation. The following paragraphs present a group of valuable ideas from the literature that are included in the comprehensive strategy at the end of this chapter.

New modes, flexible and adaptable (such as Transportation Network Companies (TNCs) and other forms of ride-hailing, e-bikes, or e-scooters) have taken the mobility scene reducing evermore the demand for transit (Liyanage et al., 2019; Fishman et al., 2020). These changes in available modes that affect the transit demand should be integrated into the modeling process since many transit agencies are already working to restructure their network and integrate new mobility options with their service (Byala et al., 2021). One of the options currently available is establishing partnerships with TNCs to complement their service (Curtis et al., 2019).

Moving current transit systems towards higher ridership goals requires a new and bold perspective. This means having a financially stable organization with a clear vision and mission, support from local communities and authorities, excellent performance indicators, and transparency. The organization should also have modern vehicles integrating clean technologies, regular maintenance, smooth rides along uncongested routes, flexible operating policies with supplemental modes to reach farther than previously thought necessary (first and last mile), and service policies that put the customer first (Rico, 2012).

First and last mile (FLM) connections could attract additional riders but require careful implementation to ensure coordination between the mainline vehicles and the connecting options for the FLM (Boarnet et al., 2017; Mo et al., 2018; Raghunathan et al., 2018). Some transit agencies have already developed specific plans to successfully integrate this strategy to increase ridership (Mohiuddin, 2021). However, the implementation must be carefully threaded to avoid undesired outcomes. Flexible Public Transportation Services such as Demand Adaptive or Deviated Fixed-Route Transit (DFRT) strategies also require careful consideration to be a cost-effective solution (Yang et al., 2016). DFRT has also been implemented in various cities to connect rural and urban areas with a service that has some flexibility to better serve users who live or work close to the primary route alignment (Potts et al., 2010).

The strategies developed to increase ridership in transit systems should also be user centered. Dervilla et al. (2016) indicated that a human-centered approach is required to improve our urban infrastructure and gather the demand characteristics that make transit, walking, and cycling attractive to all users. For example, Pipicano (2018) presented a design framework to incorporate the user perspective in the design process of structured transit networks. Therefore, it is essential to develop behavioral models combined with sound transit systems to create travel experiences that are coherent and logical for the user.

From the modeling perspective, researchers have stressed the importance of considering spatial effects in transportation planning integrating GIS-based spatial regression models (Lopes et al., 2014)

The system in Mayaguez is provided free of charge. Therefore, one way to make it more attractive is by offering rider incentives such as complimentary rides on e-bikes or even small reductions in taxes according to a ridership loyalty program. The literature provides ample evidence that reducing the number of vehicles by a small percentage will significantly impact congestion reduction (Bull, 2003; Anderson, 2013; Cambridge et al., 2005). Therefore, providing riders with incentives could take them out of the streets and into the transit system. This is one of the alternatives that will be explored as part of the focus group.

Comprehensive Strategy

A comprehensive strategy should integrate the following ideas:

- Develop a user-centered transit network with dedicated right-of-way and high-frequency vehicles, considering the potentially attracted demand. Similarly, decide the type of vehicle and the coverage area for feeder systems.
- Ensure that each transit system component is working at its best to reclaim passengers and attract new ones. These components include the roadways and stop infrastructure, the condition of the vehicles, favorable operating hours for users, committed drivers, and a robust service-oriented agency managing the system with precision and quality.
- Develop marketing campaigns of the transit system to attract new users and make sure that transit routes and services are well known for all the stakeholders involved in the transportation system.

- Implement a cell phone application with a real-time passenger information (RTPI) system that provides adequate system information and accurate projections of vehicle arrivals at stops and gives users confidence in the transit system's punctuality, efficiency, and effectiveness.
- Develop agreements to coordinate with Transportation Network Companies (TNCs) to expand the reach of the network to neighborhoods located beyond the stops of the established fixed routes and that operate as first/last mile operators. This coordination would also be convenient with payment systems for e-bikes or e-scooters that can be reserved by users in advance of the trip.
- Develop a robust planning process including planning models that consider the spatial effects of demand as part of the process.

To implement the integrated strategy presented above, the agencies managing the transportation system must get the financial resources required to embark on such an endeavor. Elected officials should be on board and committed to reducing traffic congestion and using transit as a primary strategy to reach that goal.

Chapter 9. Conclusions and Recommendations

Conclusions

- After finalizing the second year of development, the OBA servers were actively running as a Docker container service. One Bus Away as an open-source solution was able to offer valuable information for users. The supplementary services supporting OBA were also updated to be hosted on their respective containers. The development demonstrated how these services could operate with minimal load. They were able to handle user traffic peaks with low latency, effectively achieving one of the main objectives of this development.

- The results of the first focus group indicate that most users of the transportation system were older people who were captive passengers due to their age, not having a car, or not having a license. Many of the participants expressed that the lack of signage, protected stops, and knowledge about how the system works discouraged them from using it. Others stated that the location and lack of security at the stops made them uncomfortable taking the bus.

- The results of the second focus group indicate that the improvements necessary to motivate the use the transit system are: the incorporation of more readily available information, like signs and promotional information. Due to the lack of this information, some participants did not have prior knowledge of the transit system's operation. Some participants said that since the transit system's operating hours are from 6 am to 6 pm, the workers who leave later could not use the transit system to return to their homes.

- The survey conducted from April 2022 to September 2022 provided valuable insights into the demographics and preferences of participants regarding public transportation in the city. Age distribution revealed significant participation among individuals aged 18 to 24 (37.64%), followed by those aged 65 to 85 (20.30%). Gender distribution showed a slight predominance of male participants (52.59%) over female participants (46.67%), with a minority choosing not to disclose or identifying as non-binary (0.74%). Regarding transportation modes, private vehicles were predominantly used across most routes, except for specific instances where walking was a notable alternative, particularly on Route 348. Household income distribution highlighted a majority (51.15%) earning less than $10,000 annually, underscoring the economic diversity among participants. Participants expressed varying levels of satisfaction with the Mayagüez Integrated Transportation System (TIM), with high satisfaction levels reported across all routes. Concerns about service reliability were minor, with issues such as bus arrival times cited infrequently. Safety and cleanliness were generally rated positively by participants, affirming their confidence in using the system. The survey also indicated that real-time bus arrival predictions via smartphone applications would significantly influence travel behavior, potentially encouraging a shift from private vehicles to public transit.

- The total number of boardings in the TIM was 148,794 passengers in 2019. Except for the newly implemented Route 349, which had the lowest boardings that year with an average of just 592 people per month, most of the routes had monthly averages of between 2,000 and 3,000 passengers, and for all routes, the daily average ranged from 28 to 133.

- Related to the correlational analysis, the significant positive correlation between the number of boardings and the presence of multiple stops in an area (0.596***) suggests that areas with more bus stops tend to have a higher number of boardings. This is because greater accessibility and availability of stops facilitate the use of public transportation. The population also shows a significant positive correlation with the number of boardings (0.469***), indicating that areas with higher population density result in greater use of public transportation. This makes sense, as a larger population increases the demand for transportation due to residents' mobility needs. Areas with a higher average age tend to have fewer boardings, possibly because older individuals might depend less on public transportation due to reduced mobility or a preference for other modes of transportation. Median household income shows a significant negative correlation with the number of boardings (-0.314**). Areas with higher median incomes tend to have fewer boardings, suggesting that wealthier families might prefer using private vehicles over public transportation. The negative correlation between the average number of vehicles per household and the number of boardings (-0.209) is not significant, but it suggests that more vehicles available per household reduces the need to use buses. The significant negative correlation between the average number of people over 60 years old in households and the number of boardings (-0.381***) suggests that areas with older individuals tend to have fewer boardings. Older individuals might have different mobility patterns and depend less on public transportation.

- The results of the analysis of the Boarding variable in the bus stop areas and the neighboring of each stop yield a coefficient of 0.1316. This Result of Moran's ***I*** value indicates a weak positive spatial correlation, suggesting a slight tendency for high boarding values (stops with many boardings) to be near other high values and low values to be near other low values. This means that a high boarding at the neighboring bus stop is related to the boarding at the reference stop. However, this clustering is weak, indicating that either there is no spatial correlation, or the spatial correlation is due to other factors that were not considered and that could be found in a spatial regression analysis.

- The Moran's ***I*** coefficient for the spatial regression analysis is 0.3043 with a p-value of 0.00317, which indicates a significant spatial autocorrelation in the residuals, however, the most significant model variables were not those related to the spatial analysis such as variable *lagx*. Pop with a significance of 0.1 and *lagx.HouseHold* which turned out to be not significant. This indicates that although the model serves to predict boarding considering neighboring variables, the *lagx*. Household variables alone do not explain part of the passenger behavior related to boarding.

- The spatial regression analysis reveals that the number of stops in the area, vehicle ownership, and the presence of multiple stops positively influence public transport usage. Conversely, higher average age and median household income negatively impact boardings.

Recommendations

- To acquire specific data on user trip behavior, a new application should be developed, focusing on the types of data to be extracted from users. The current REST APIs allow for the integration of new connections and third-party software.

- Enhancing transportation infrastructure in areas with fewer stops could increase the number of boardings, promoting more efficient use of public transportation. Improving comfort and efficiency to enhance system convenience could attract public transportation use in higher-income areas. Programs aimed at older adults, focusing on accessibility and comfort, could also boost public transport usage.

- The slight positive correlation of neighboring populations in boarding numbers at reference stops underscores the importance of interconnecting adjacent areas. Planning efforts should ensure that transportation networks are well integrated, as improvements in one area could affect usage patterns in neighboring regions.

- Transportation system improvements must consider both the immediate study area and its neighboring regions. This holistic approach can design more efficient and effective public transport systems that meet the needs of the entire urban area. Low-population areas with neighboring high-population areas could benefit from better connectivity and integration with adjacent transportation networks.

- Although the effects of neighboring area variables are not highly significant, they offer valuable insights into travelers' spatial behavior concerning public transport use. Recognizing these patterns can lead to more effective transportation planning policies.

- A more exhaustive spatial analysis is recommended, including variables not considered in this study, such as congestion-related factors like average delay. This will help establish if there is a spatial relationship between these performance measures and boardings. Additionally, the use of RTPI applications like OBA could be analyzed to determine if such applications have a spatial effect on ridership.

- Conducting a comprehensive spatial analysis will enable a better understanding of the spatial dynamics of public transportation usage and help develop strategies to improve efficiency and user satisfaction.

- By implementing these recommendations, public transportation systems can be enhanced to better meet the needs of diverse populations and promote greater use of public transit.

- Future research would be necessary to use behavioral information captured using the OBA system coupled with a georeferenced database to explore how travelers choose between public transit, TNC services, and other methods (e.g., micro-mobility) and how to influence this behavior. We believe that a better understanding of the choice behaviors can shed light on how public agencies can regulate and partner with new mobility services; how mobility service providers can better support transit operations (e.g., route replacement, optimization, seamless mobility platforms for routing, booking, and payment); and how best to "message" travelers in real-time (via texts, emails, etc.) to nudge them toward making congestion reducing travel choices like taking public transportation. Also, collaborating with the city of Mayagüez will allow us to use it as a testbed to develop suitable strategies for a medium-sized city with urban and rural transit systems.

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Appendix A: Survey Results

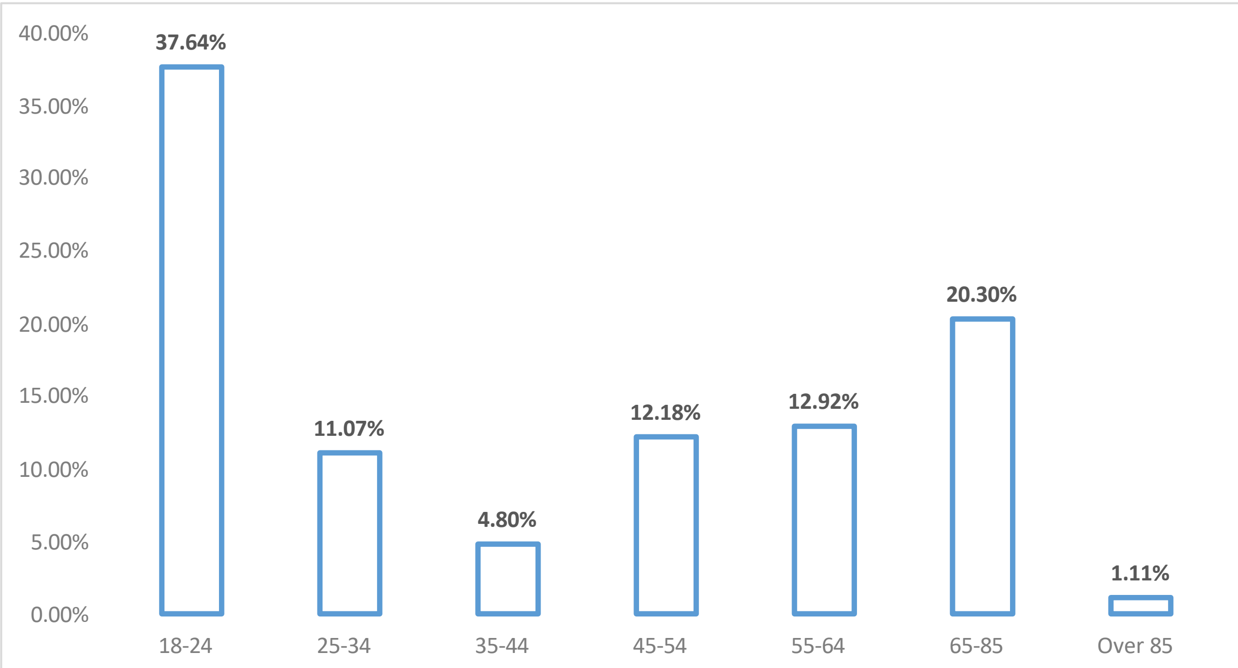

Figure 23. Q01. What is your age?

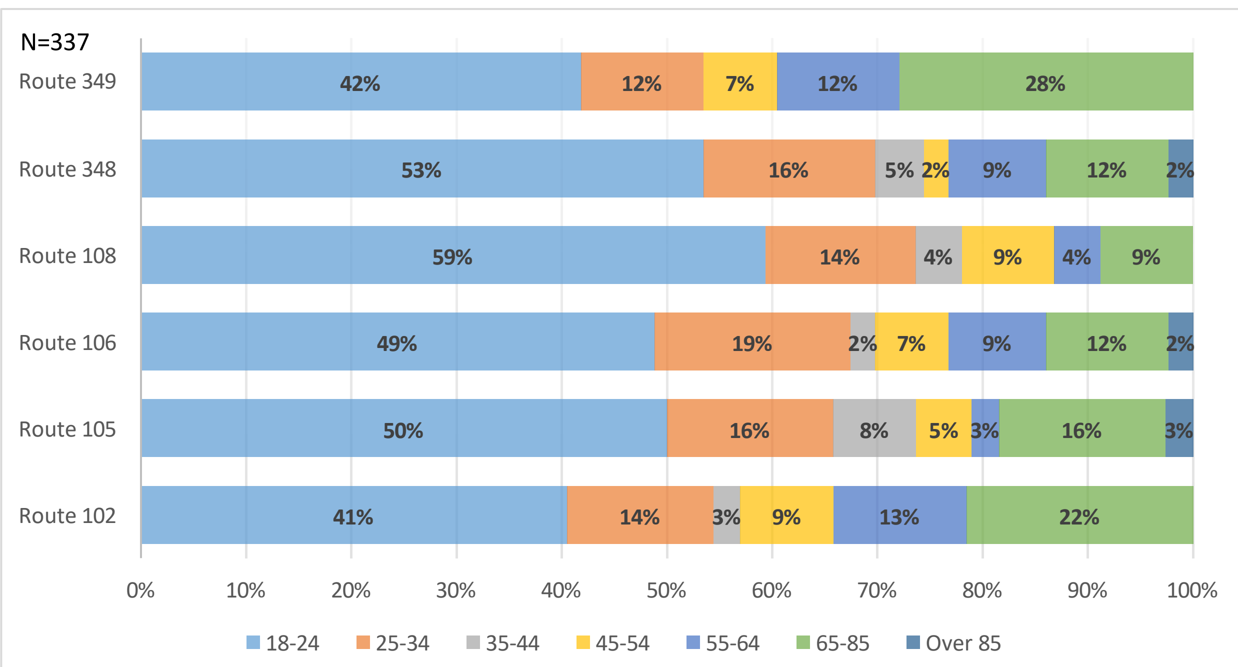

Figure 24. Q02. What is your age? / per route

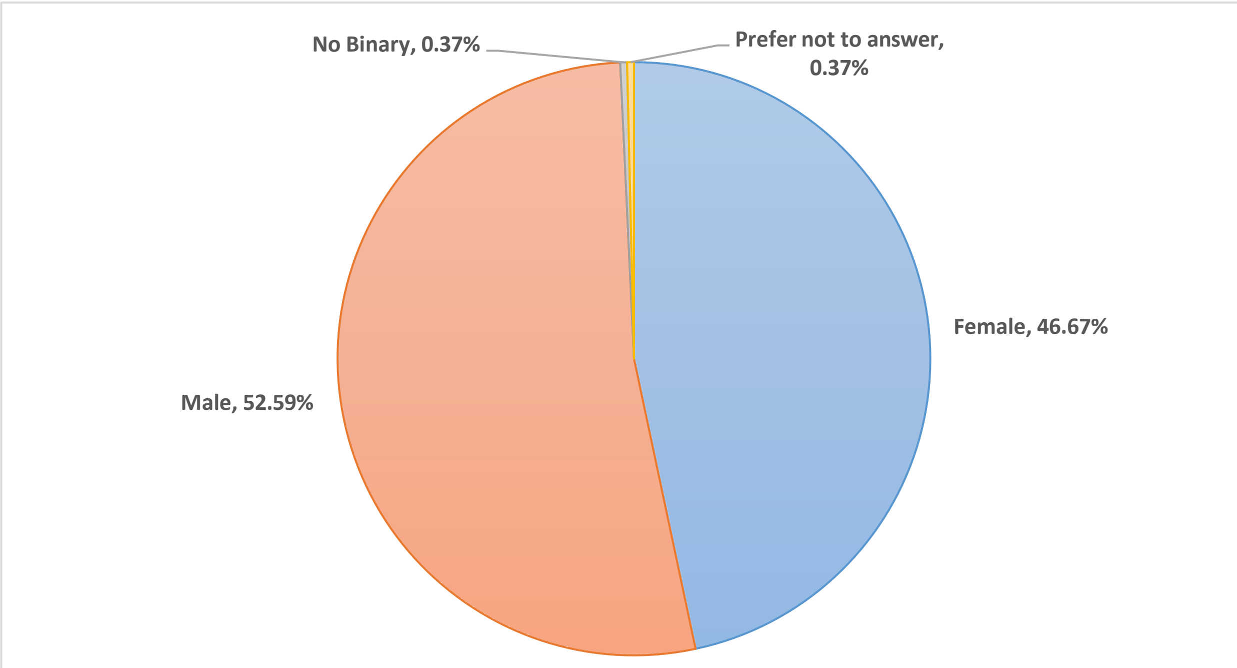

Figure 25. 03. Gender

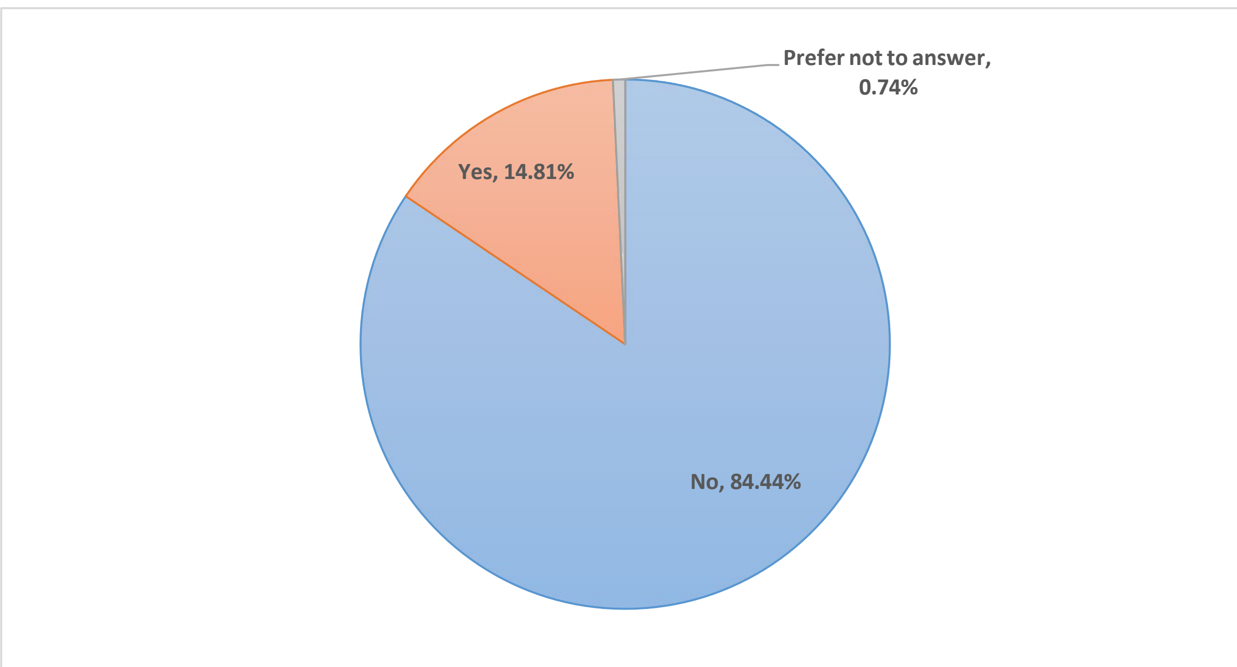

Figure 26. Q04. Do you have any type of disability?

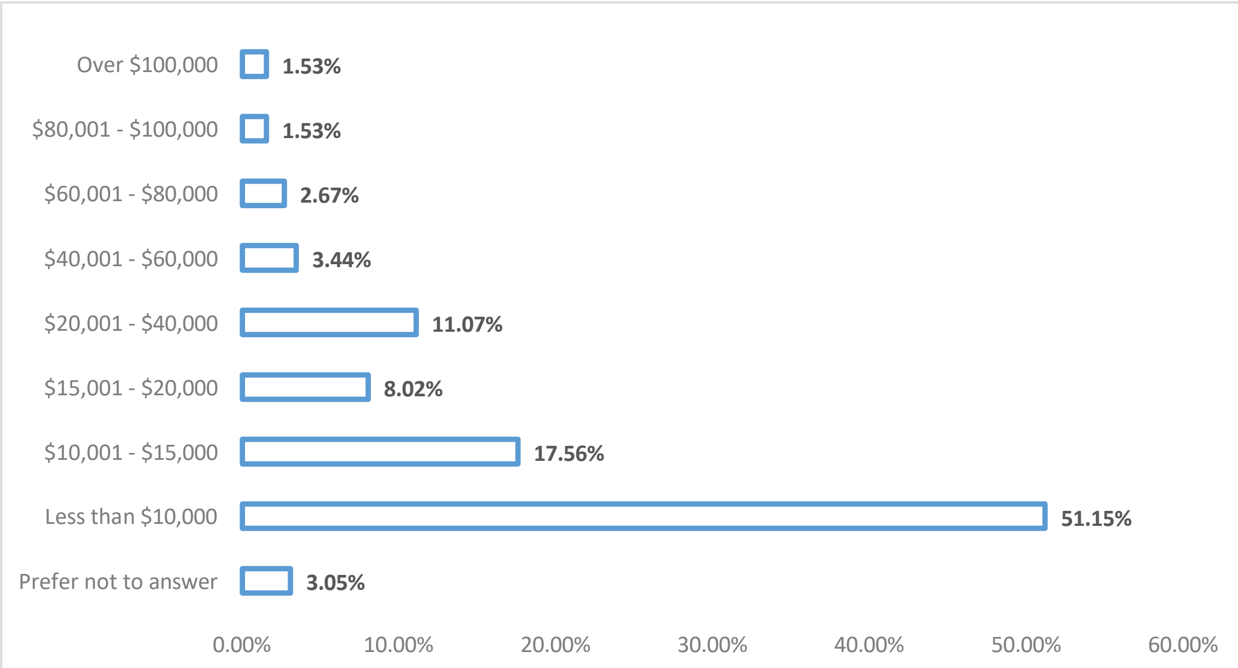

Figure 27. Q51. What is your annual household income?

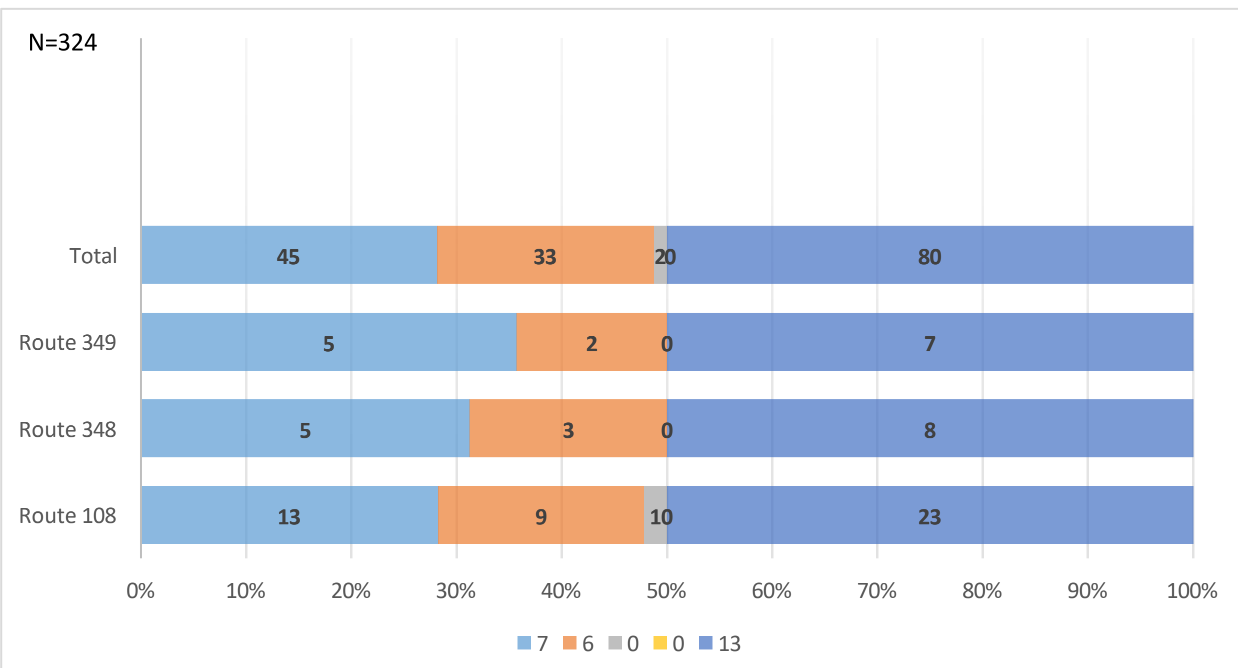

Figure 28. Q12. How many people live in your home?

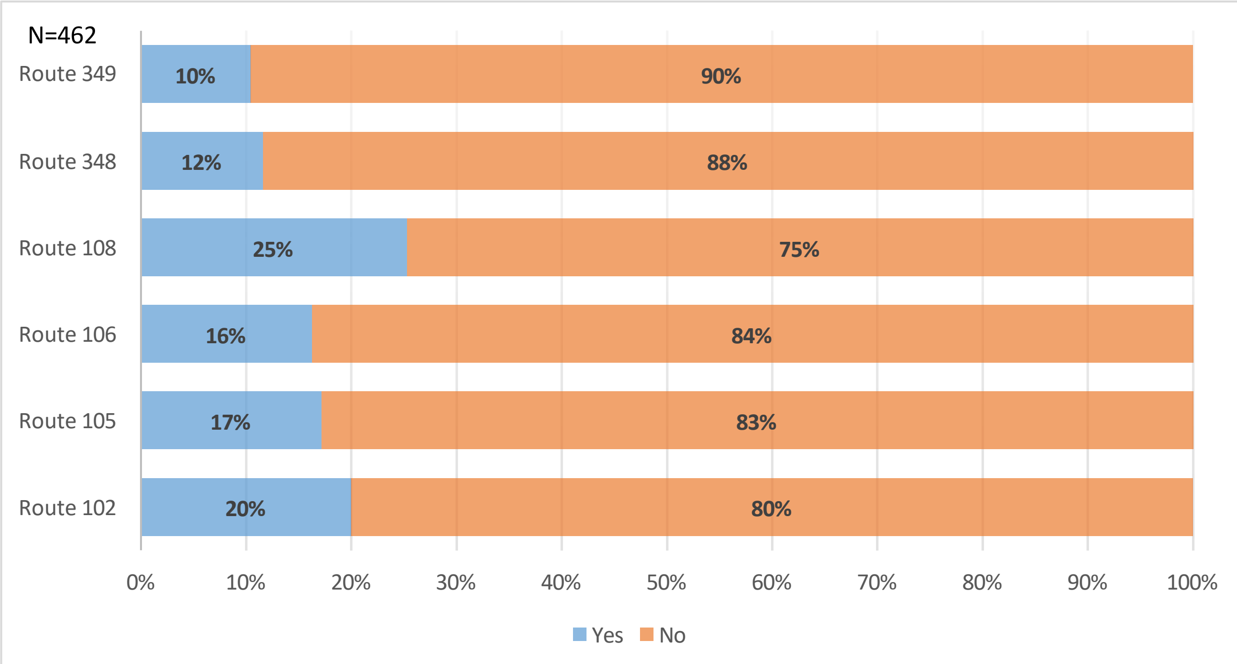

Figure 29. Q14. Have you used the Mayagüez Integrated Transportation System (TIM) in the past year?

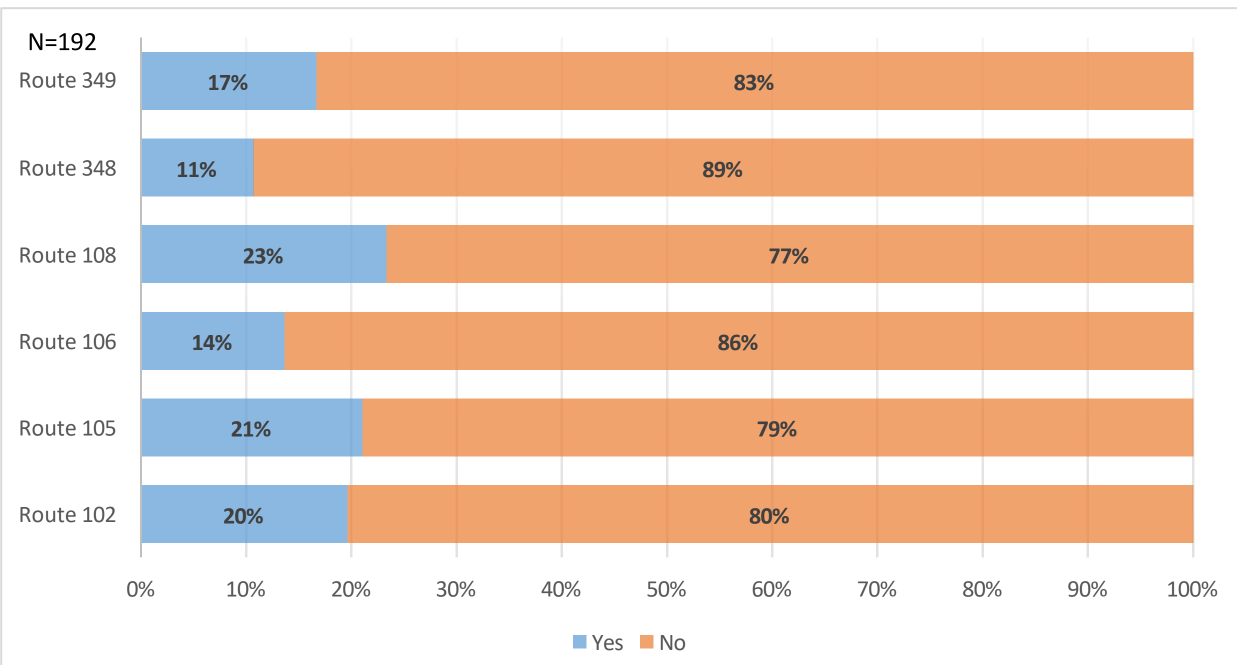

Figure 30. Q15. Have you used another transit mode?

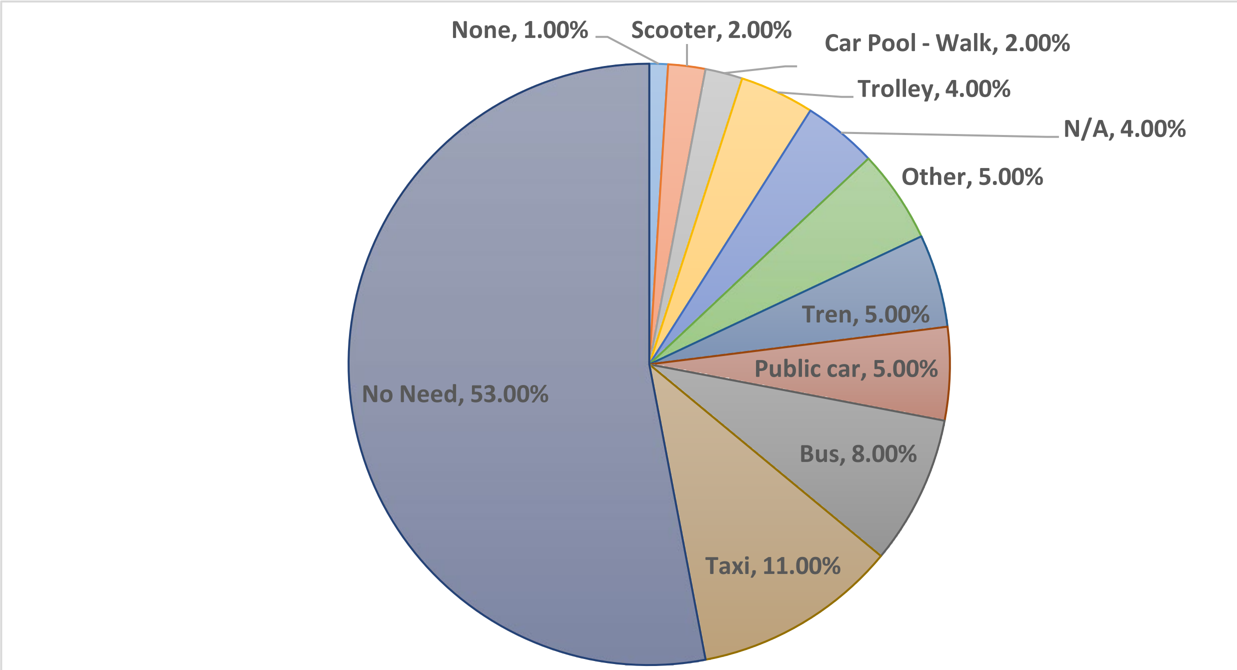

Figure 31. Q16. What means of transit have you used?

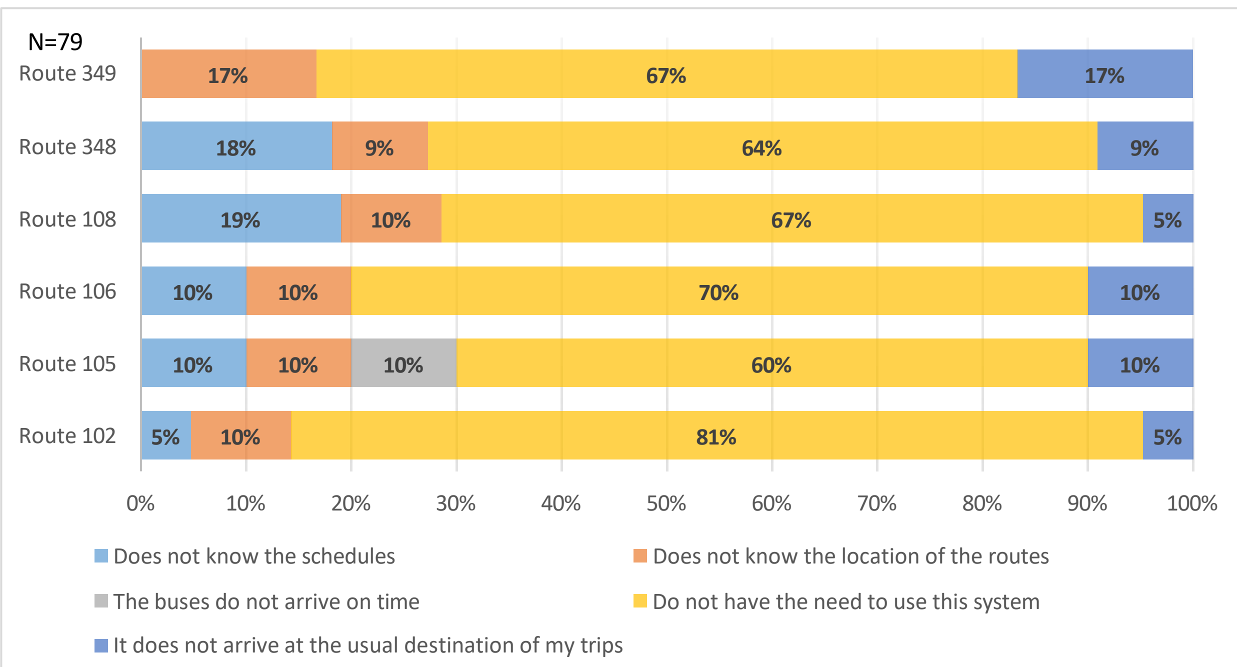

Figure 32. Q17. What is the main reason why you have not used the Integrated Transportation System in Mayagüez?

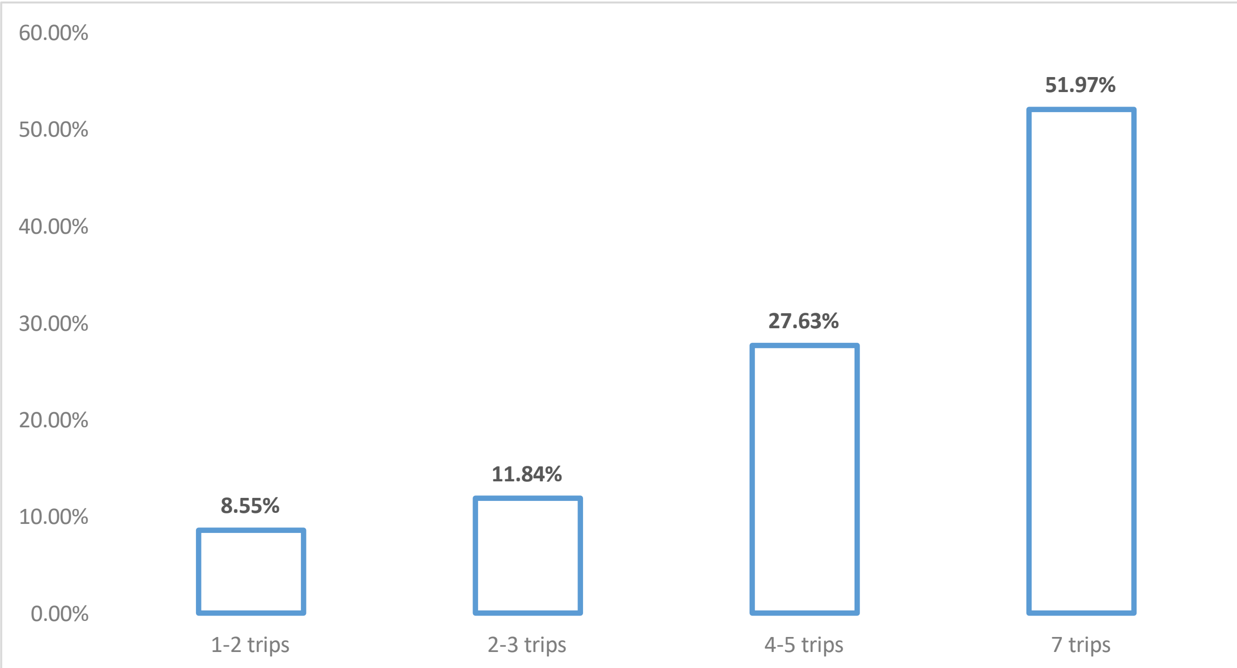

Figure 33 Q18. How many trips do you typically make in a week?

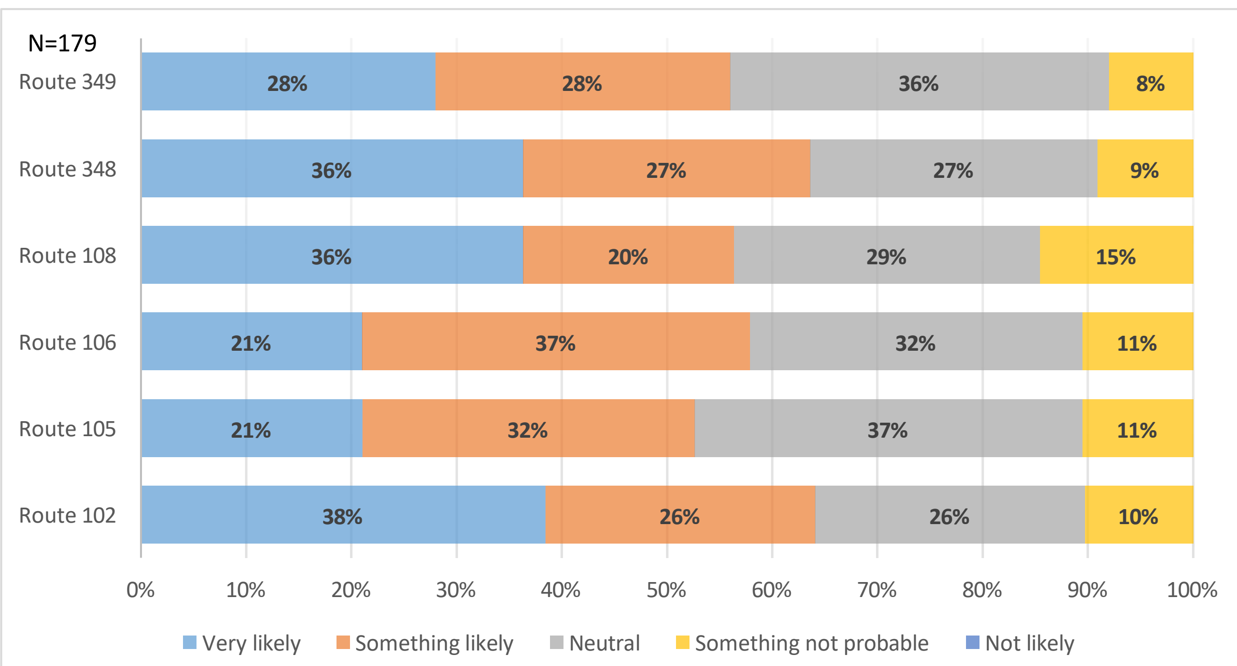

Figure 34. Q19. Consider that you are going to make a trip within the routes of the TIM. How likely is it that you would leave your private vehicle and use the bus service of Mayagüez if you had an application on your cell phone that provides you with real-time information on the location of the buses and predictions of arrivals at the routes?

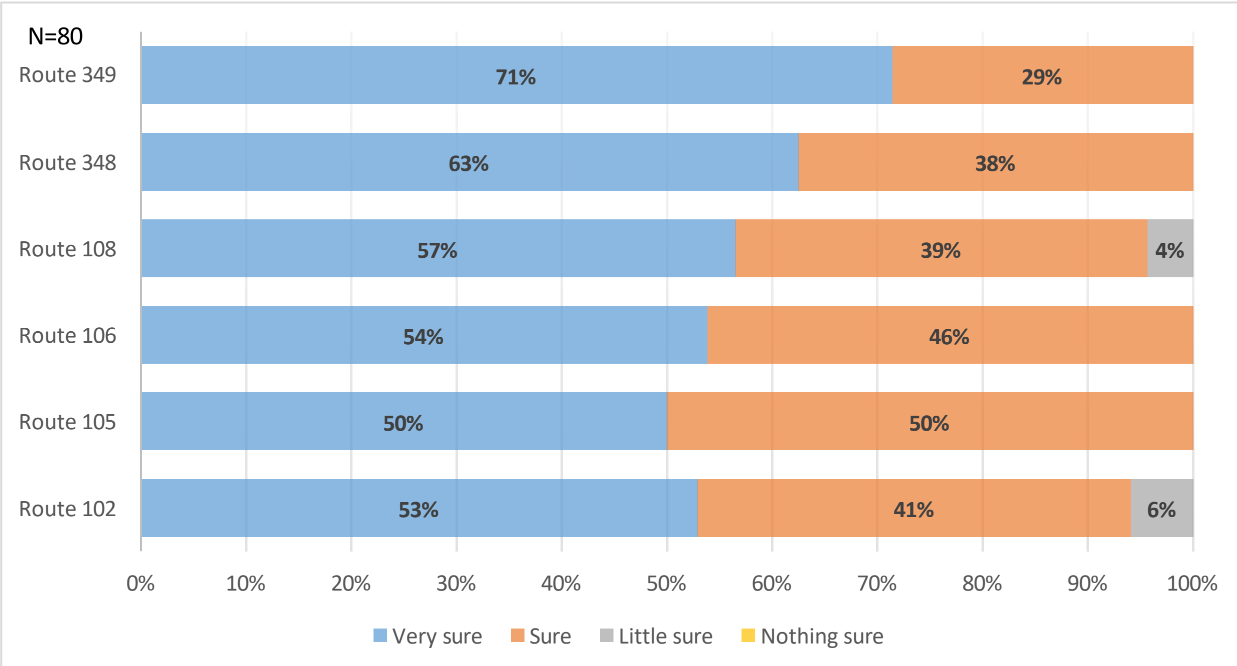

Figure 35. Q20. How safe do you feel traveling in the Integrated Transportation System (TIM)?

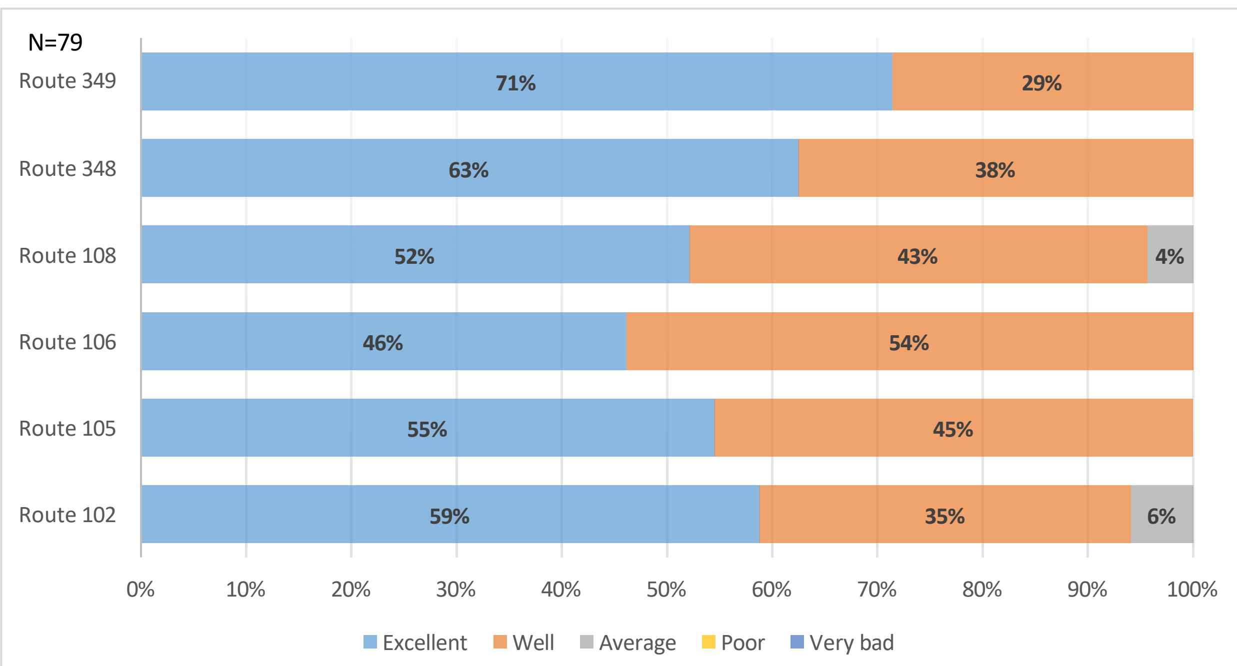

Figure 36. Q21. How would you describe the customer service provided by the bus drivers?

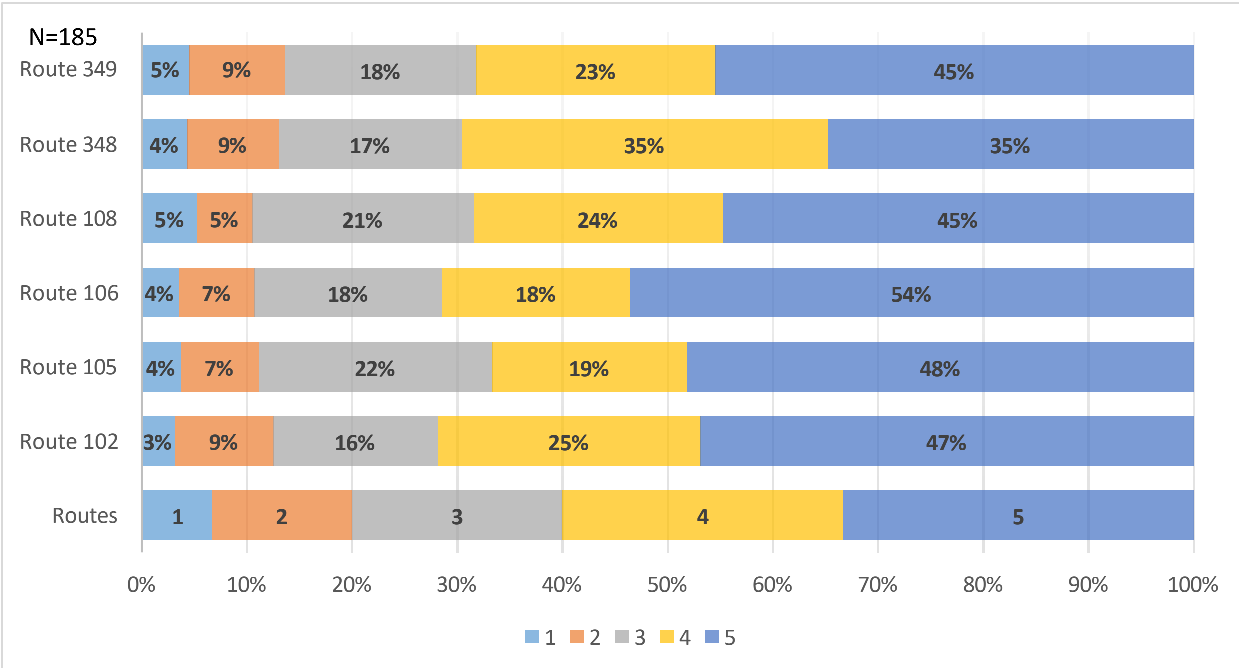

Figure 37. Q22. On a scale of one to five, with one being the lowest level, evaluate the cleanliness of the buses.

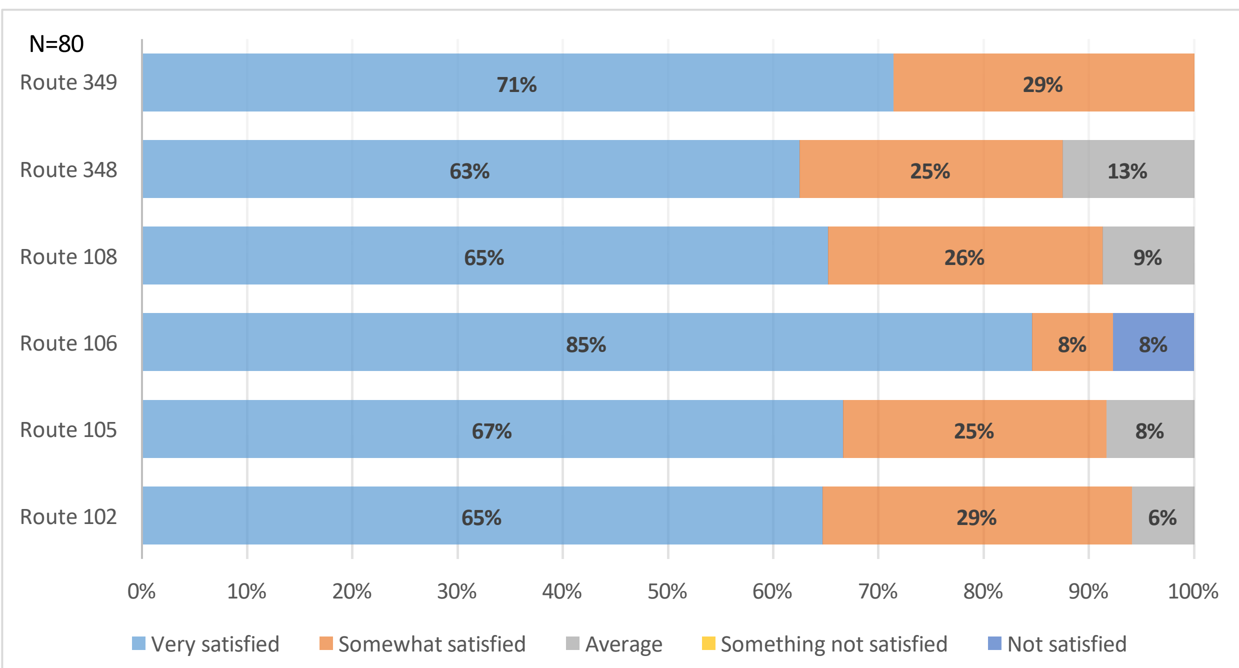

Figure 38. Q23. How satisfied are you using the Mayagüez Integrated Transportation System?

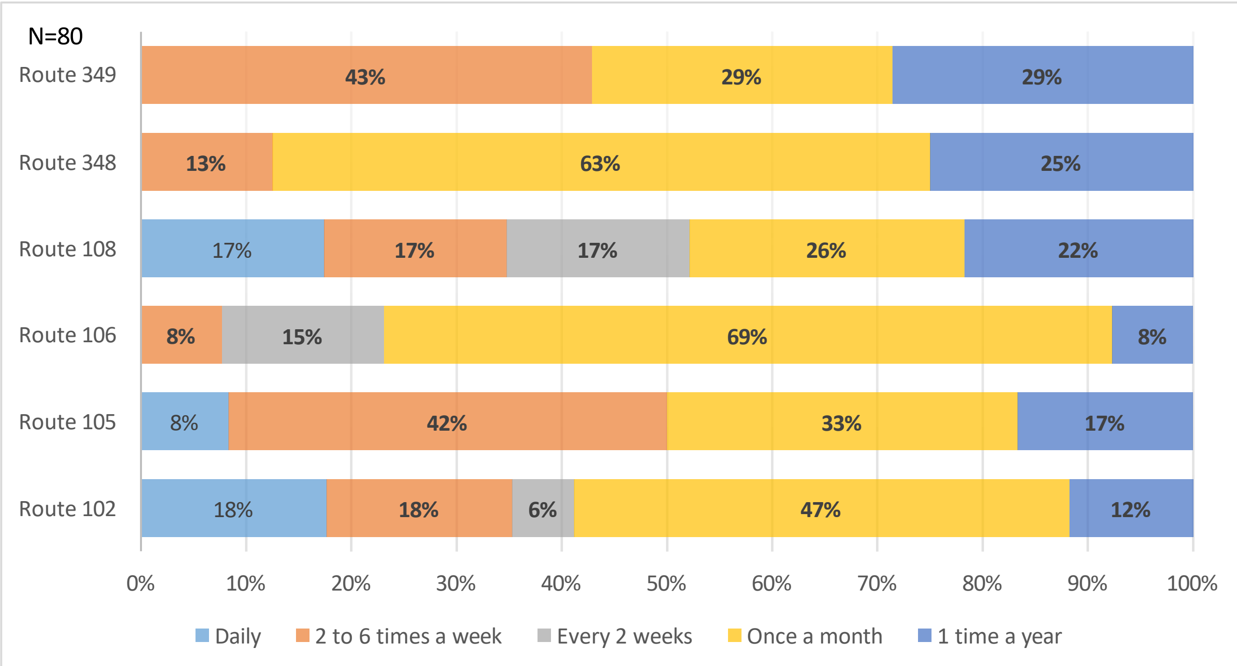

Figure 39. Q24. How often do you use transit?

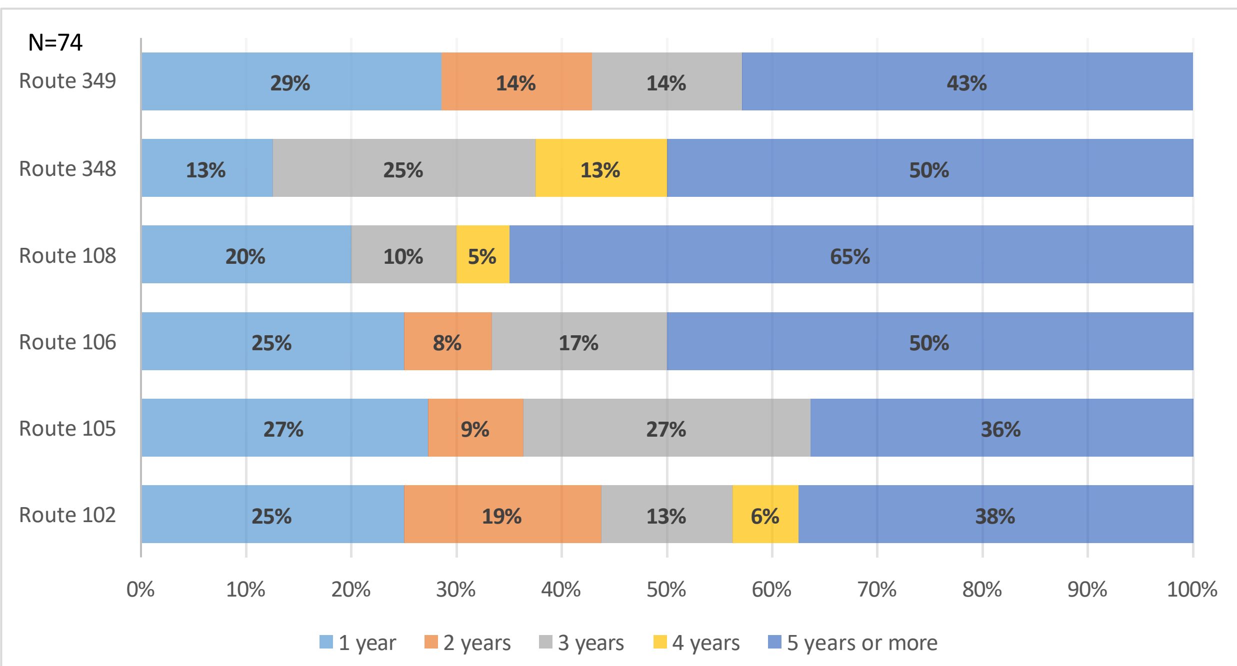

Figure 40. Q25. How long have you been using transit?

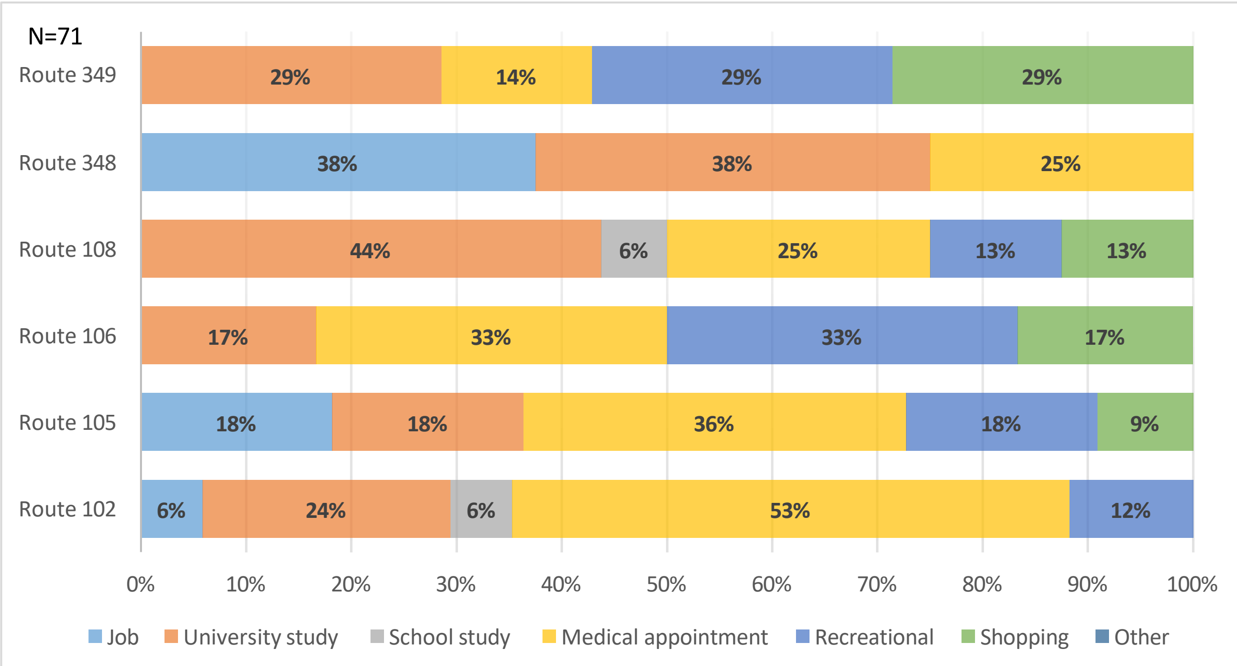

Figure 41. Q26. What is the type of activity for which you use transit?

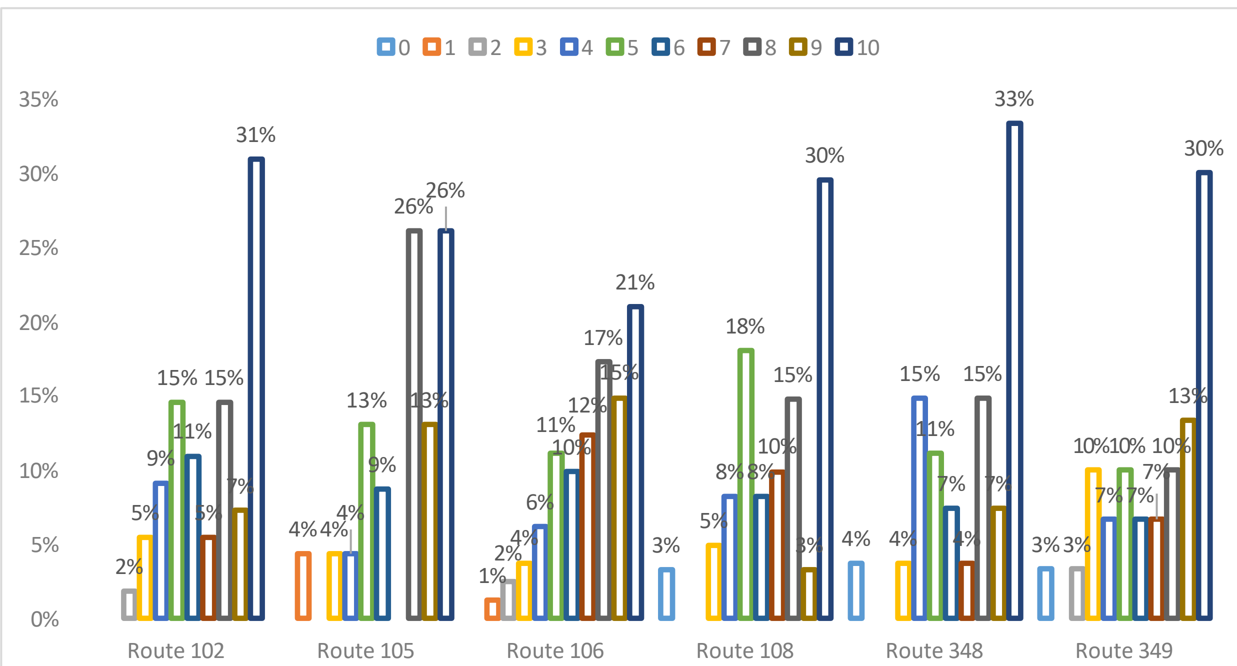

Figure 42. Q40. What score would you give to the bus stop closest to your home, from 0 to 10, where 0 is a stop that is not at all adequate and 10 a stop that is very adequate?

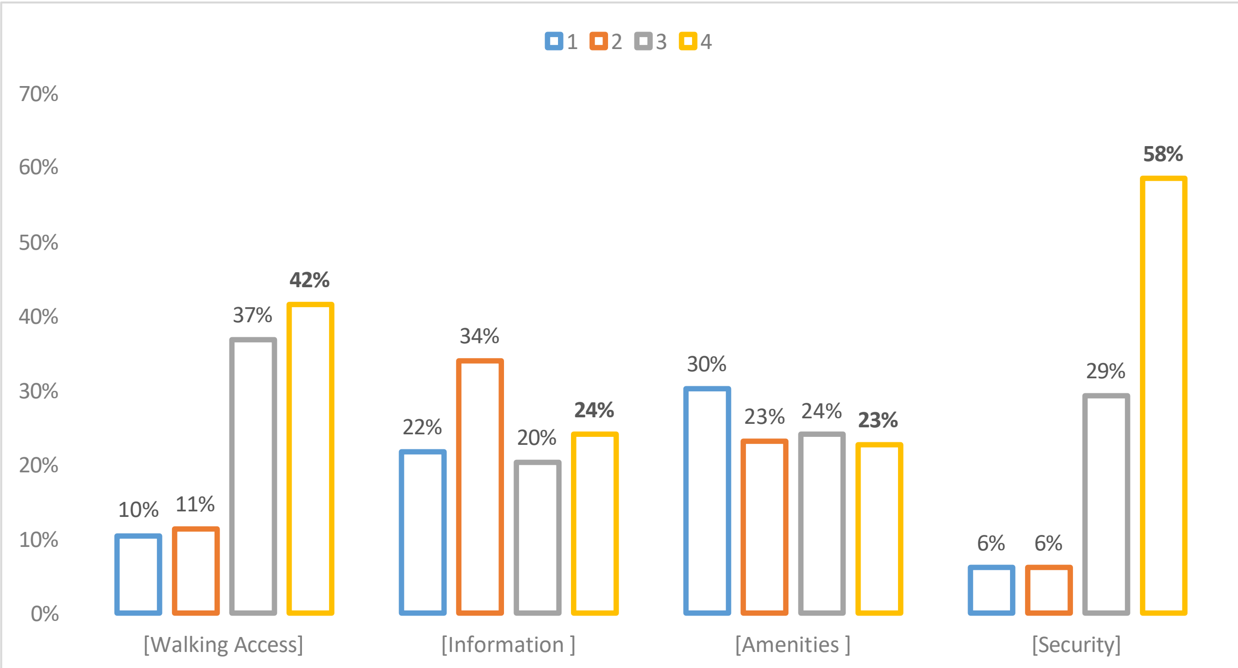

Figure 43. Q41. Order the following aspects of a stop that would be most relevant to you from the least important to the most important

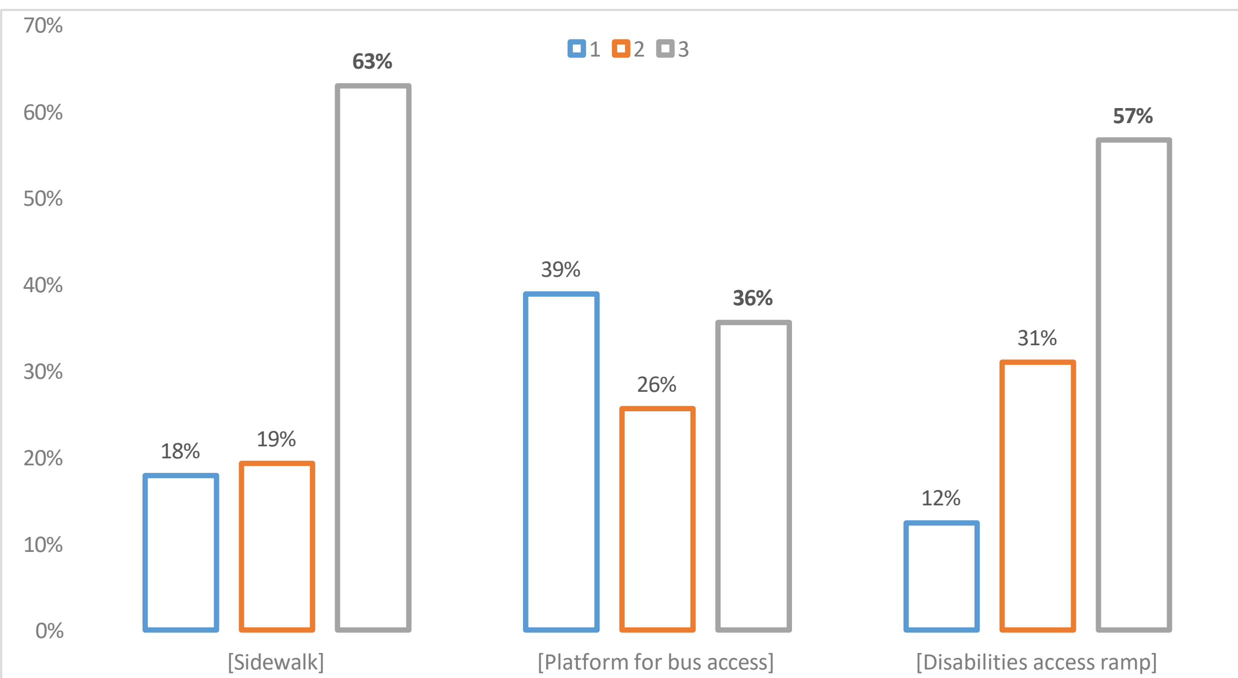

Figure 44. Q42. Order the following aspects related to pedestrian access to the stop that would be most relevant to you from the least important to the most important

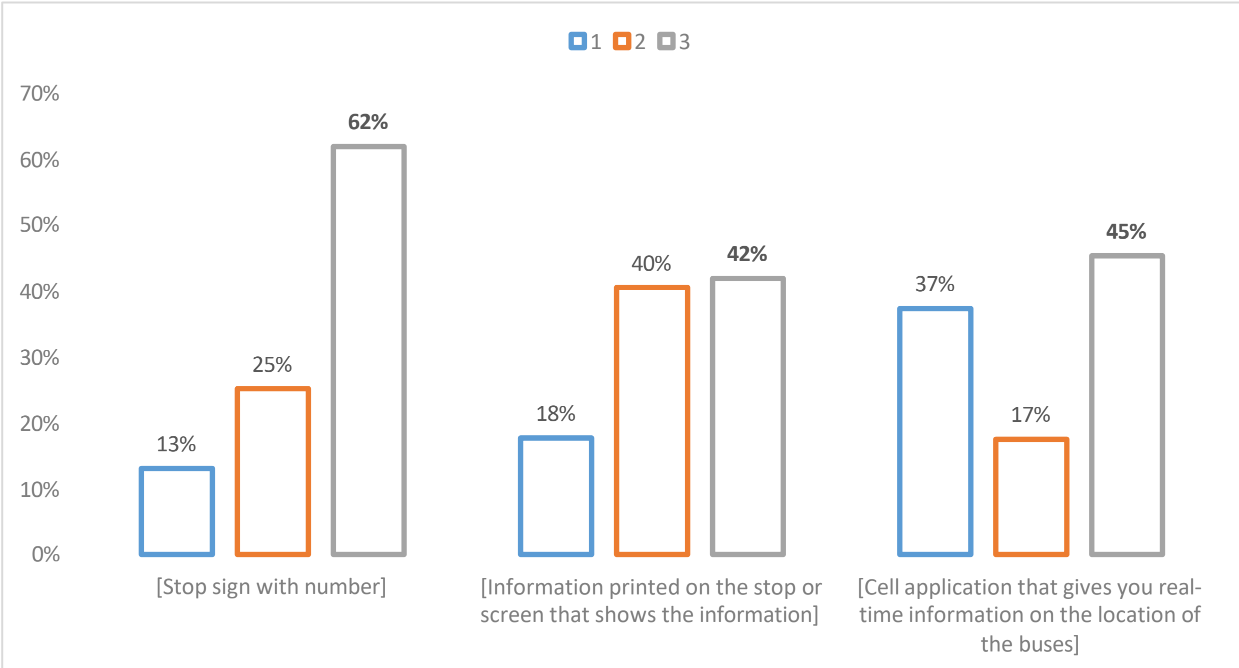

Figure 45. Q43. Order the following aspects related to the information of the pedestrians at the stop that would be most relevant to you from the least important to the most important

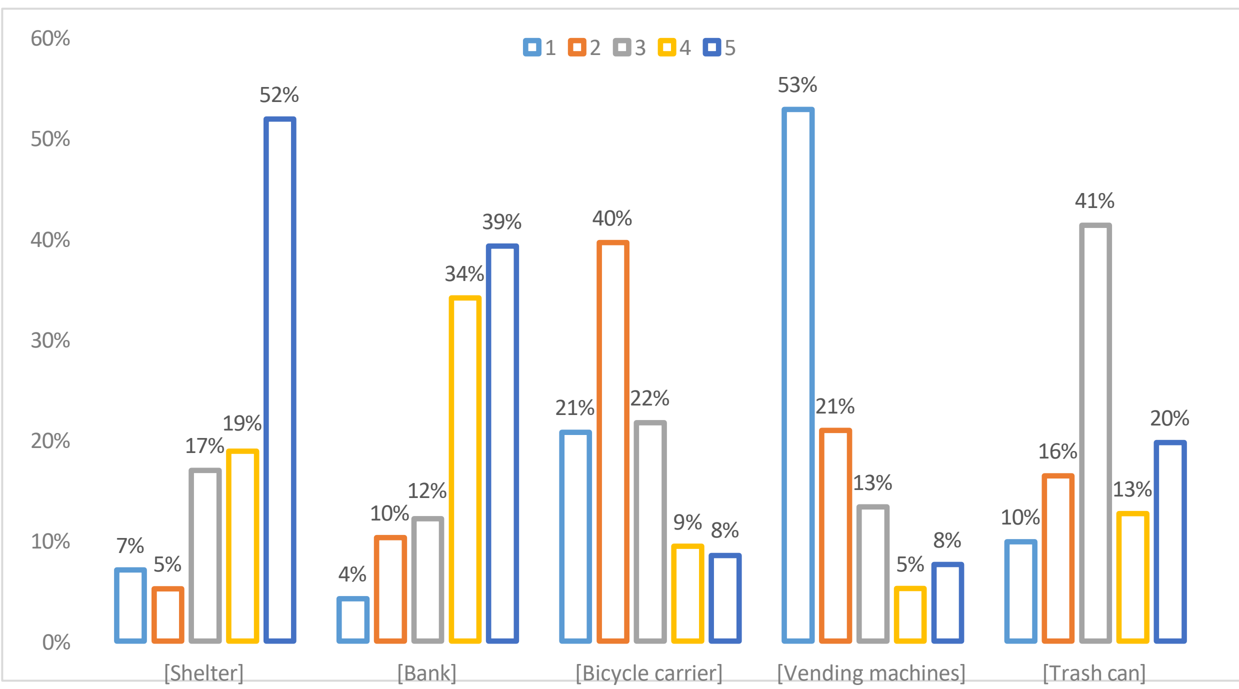

Figure 46. Q44. Order the following aspects related to the amenities at the stop that would be most relevant to you from the least important to the most important

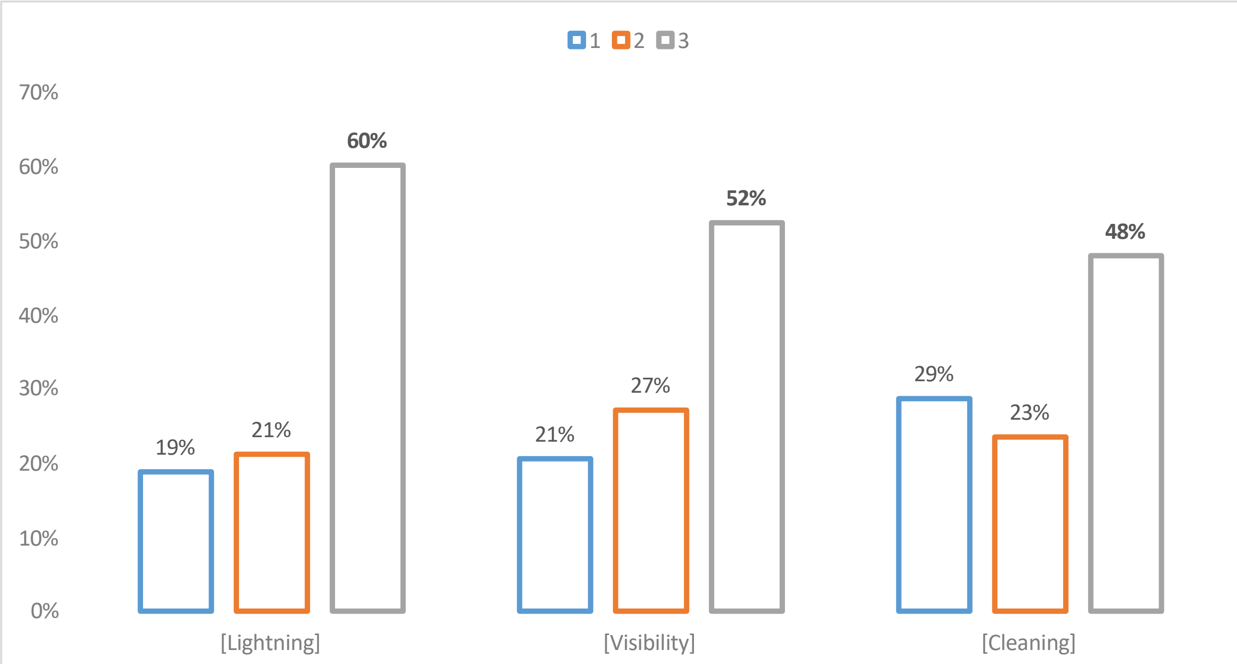

Figure 47. Q45. Order the following aspects related to safety at the stop that would be most relevant to you from the least important to the most important

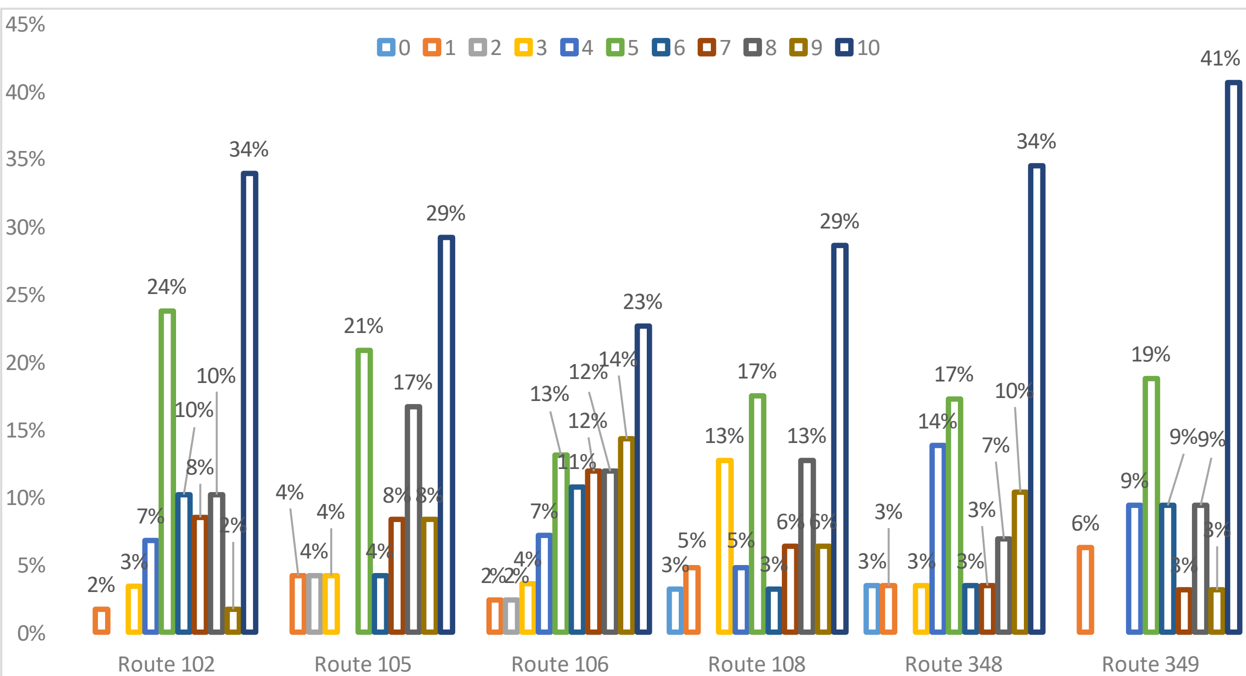

Figure 48. Q46. Considering the aspects of pedestrian access, information, amenities and security, what score would you give to the stop, from 0 to 10, where 0 is a stop that is not at all adequate and 10 a stop that is very adequate?

Table 5. Q46. Considering the aspects of pedestrian access, information, amenities and security, what score would you give to the stop, from 0 to 10, where 0 is a stop that is not at all adequate and 10 a stop that is very adequate? Statistics

Variable	Route	N	Mean	SE Mean	StDev	Minimum	Median	Maximum
Puntuation	102	59	7.000	0.337	2.586	1	7	10
	105	24	7.125	0.559	2.74	1	8	10
	106	84	7.095	0.269	2.467	1	7	10
	108	59	6.763	0.400	3.07	0	8	10
	348	30	6.867	0.552	3.026	0	7.5	10
	349	33	7.152	0.495	2.841	1	8	10

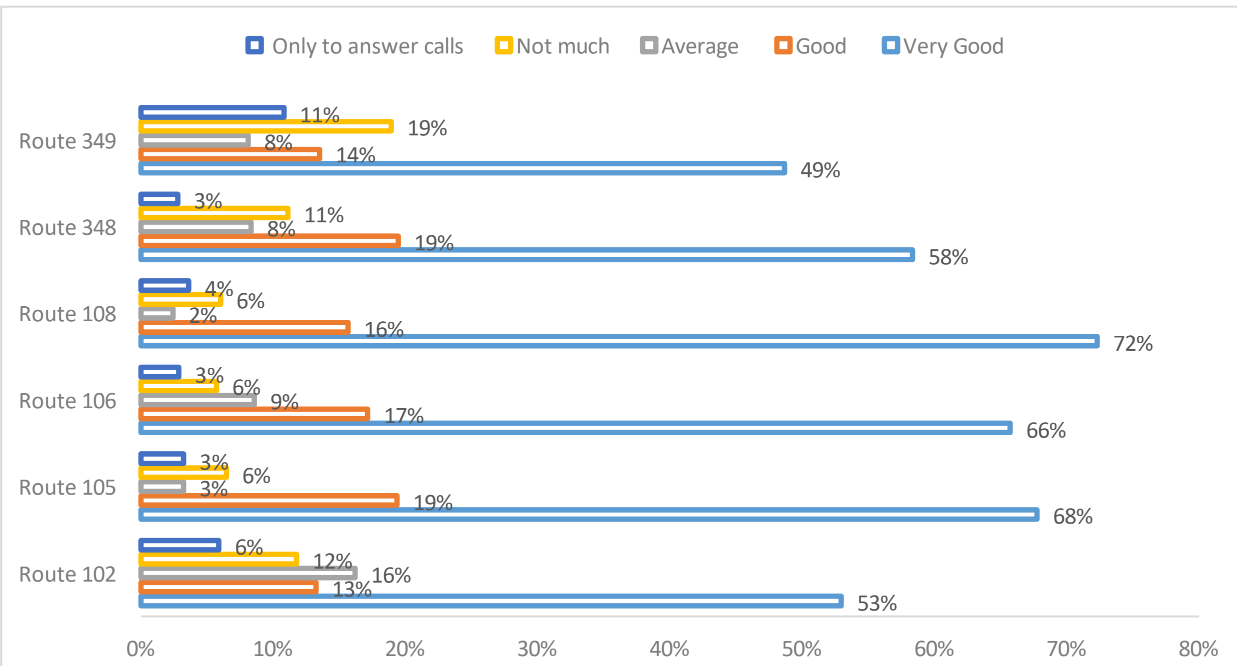

Figure 49. Q48. How well do you know how to use a smartphone?

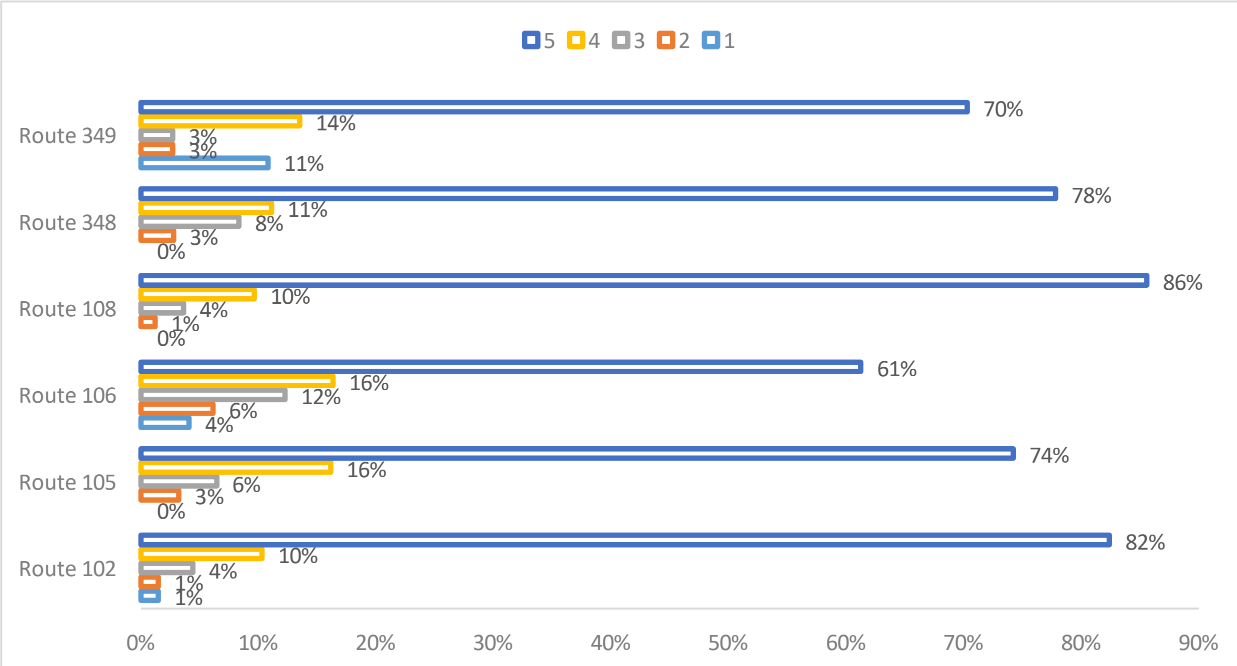

Figure 50. Q49. How useful would it be to have live-time bus arrival predictions for your trip planning?

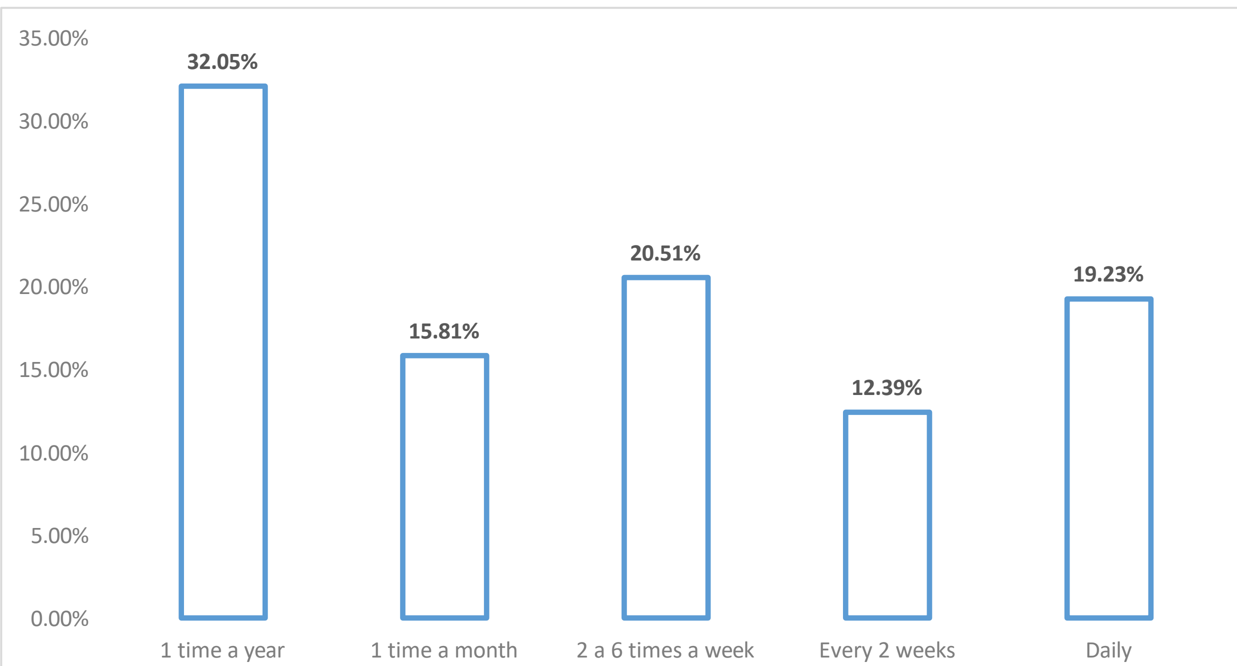

Figure 51. Q50. How often do you use mobile applications such as Maps, Google Maps and Waze to make your trips?

Appendix B: 2019 Bus Stop Surrounding Area

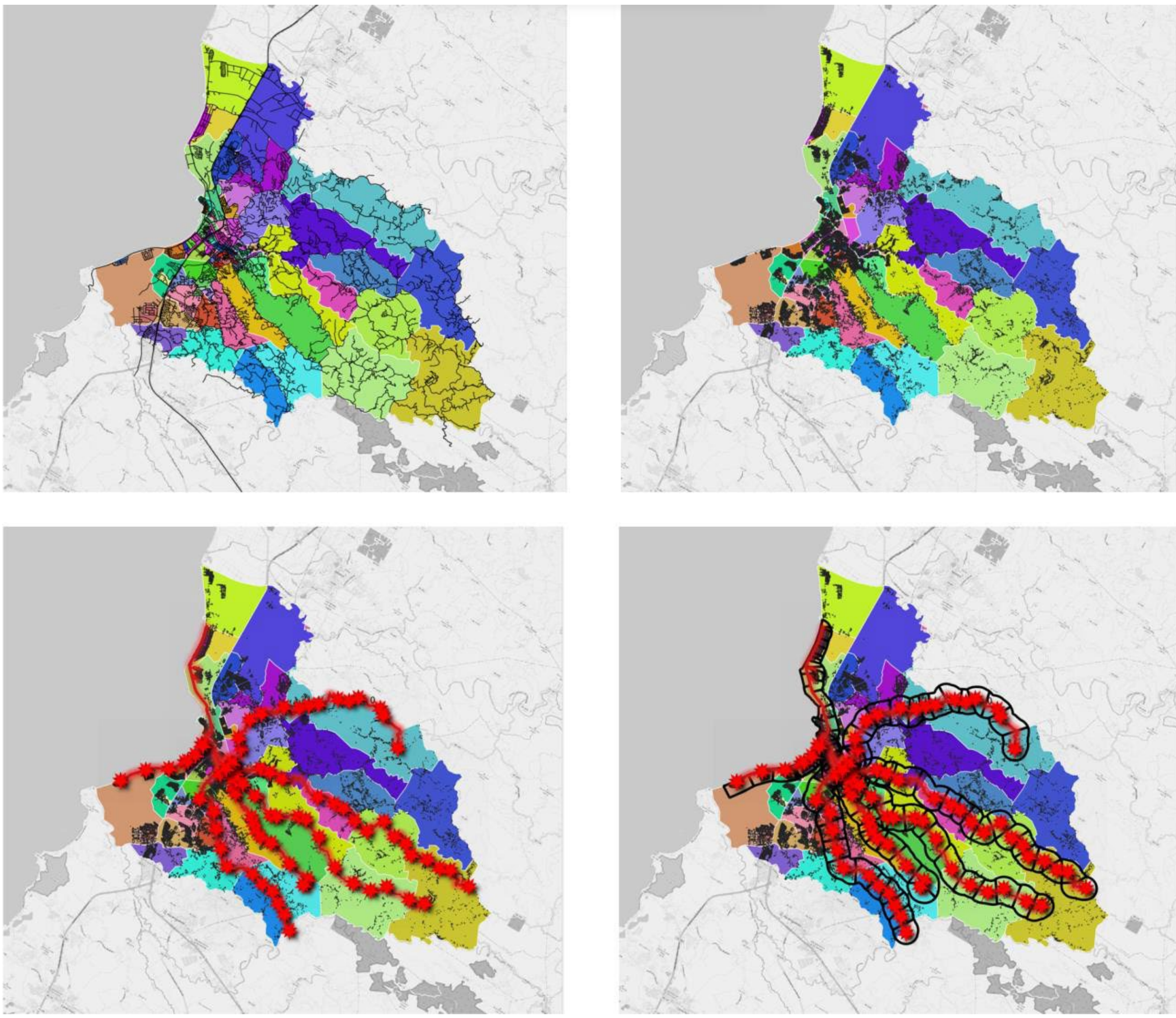

Figure 52. Initial Bus Stop Areas of the TIM

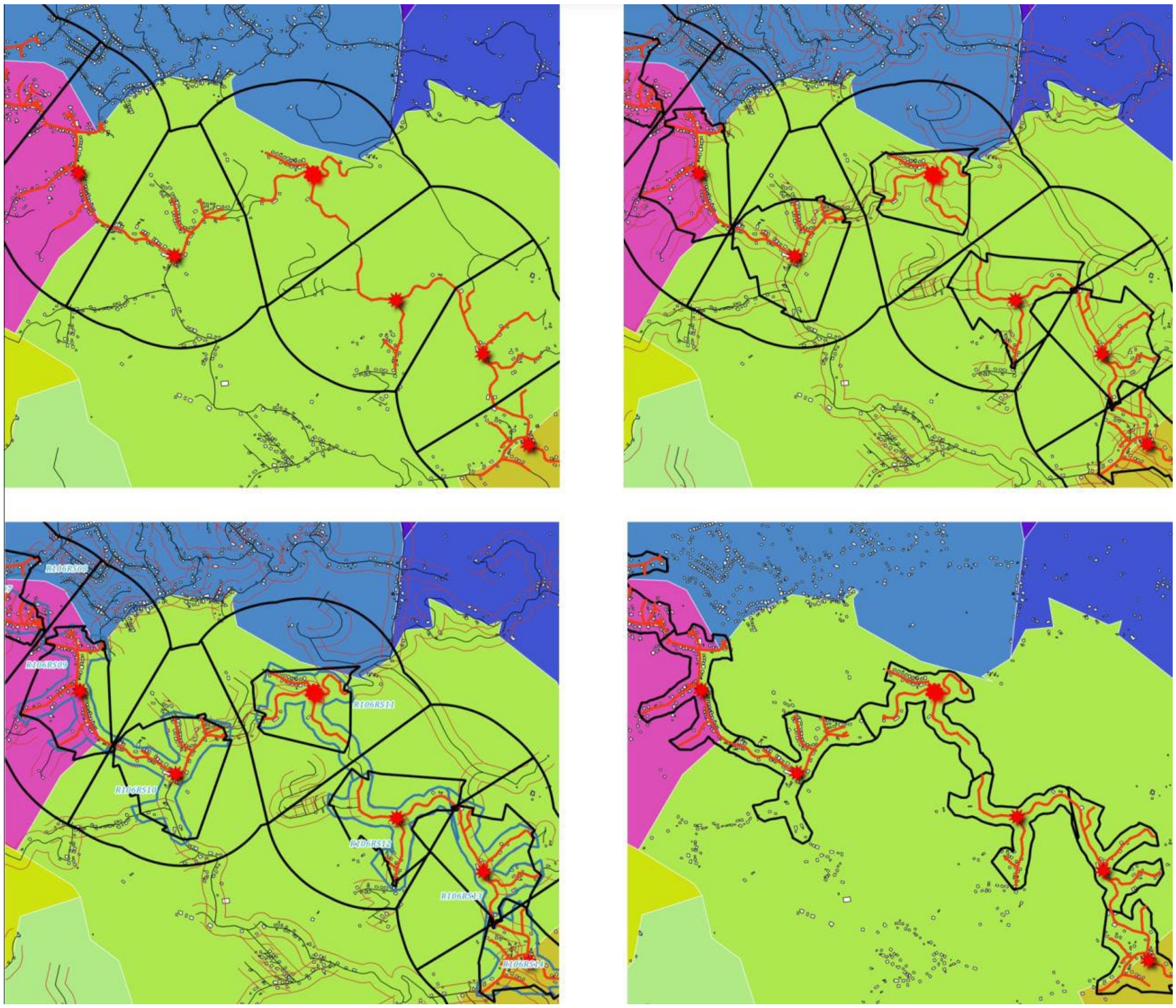

Figure 53. Bus Stop Area Delimitation Process

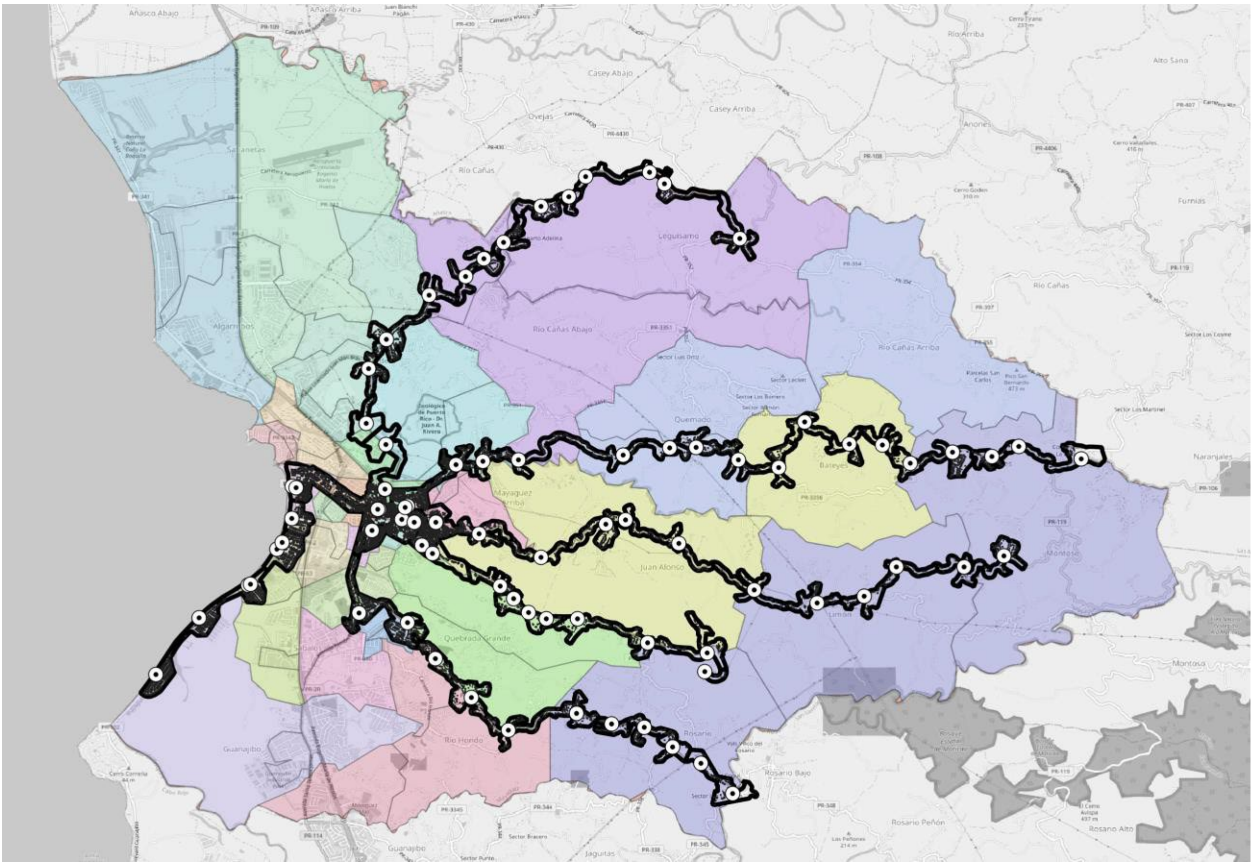

Figure 54. Bus Stop Areas of the TIM

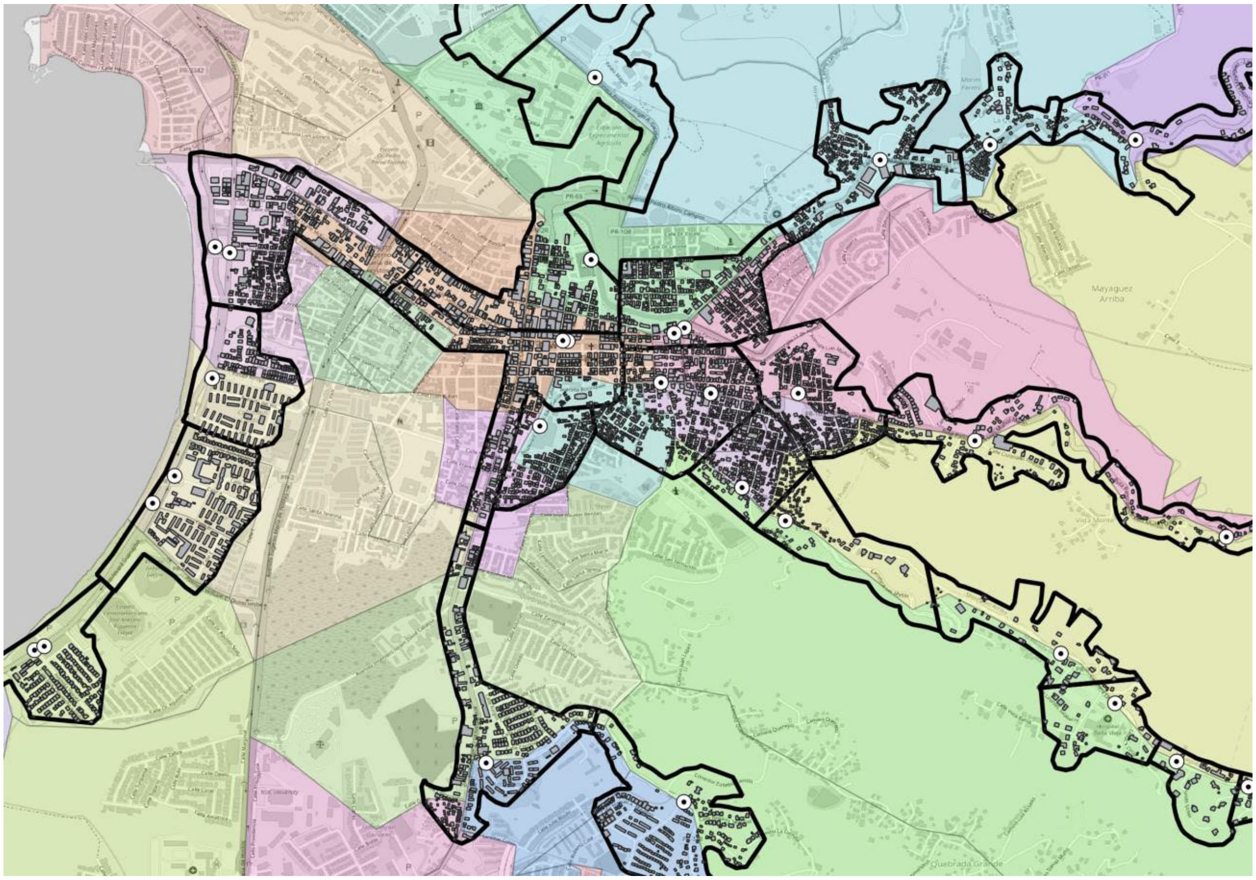

Figure 55. Zoom into some Bus Stop Areas of the TIM

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