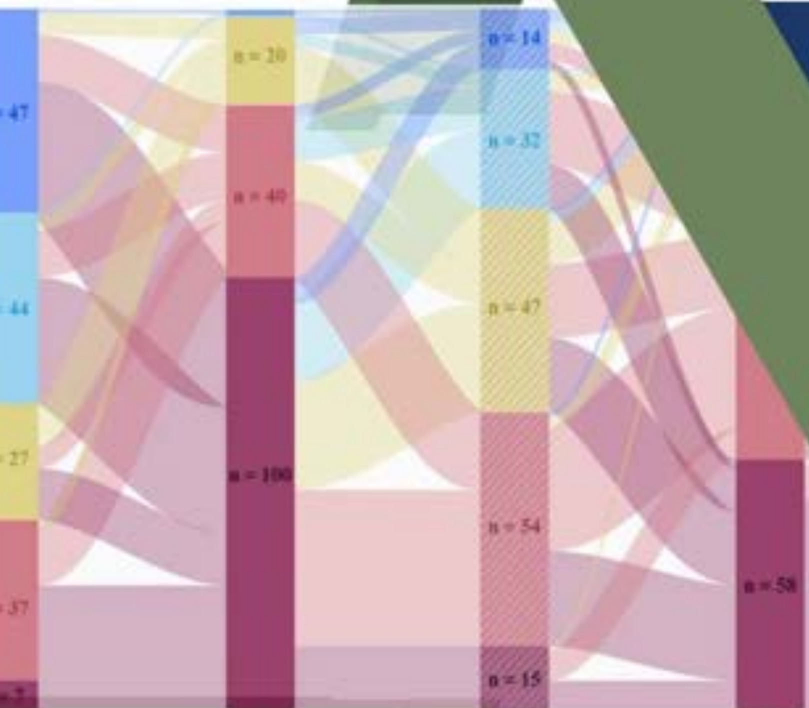

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NOVEMBER 2022

Enabling the Shared Transportation Revolution

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ABSTRACT

The transportation industry is rapidly forming an image of the future that is autonomous, connected, electric and shared. Although electric vehicles may help us make great strides in the area of point-source emissions, and autonomous vehicles may further efforts to improve safety, the congestion impacts of these technologies will be limited and may actually worsen conditions in urban areas. Although TNCs offer shared ride services, including LyftLine and UberPool, the number of carpool trips is far less than their typical non-shared services. Shared ownership of vehicles is not enough to mitigate most issues in the transportation system (congestion, inefficiencies, emissions, etc). Pushing toward shared usage is critical in urban areas, however shared usage is dependent on the ability to link travelers to one another and their willingness to share the ride. The COVID-19 disruption dramatically impacted mobility, especially shared modes such as ride-hailing, shared ride-hailing, and public transit, and presented a unique opportunity to study attitudes, reactionary behavior, and recovery. A disruption with the magnitude of the COVID-19 pandemic had the potential to bring about many short-term and long-term behavioral changes. To predict if the “social distancing” nature and resulting shifts in behavior from the pandemic continued to persist after the pandemic ends, this work examined preferences and behaviors towards shared mobility during different stages of the pandemic. Although levels of comfort using shared modes improved since the summer of 2021, participants still reported that their comfort using transit, ride-hailing, and shared ride-hailing would not fully return to pre-pandemic levels by October 2022. Understanding the impact and response from this disruption was important to aid policymakers in building a more resilient and sustainable transportation system. Creating a flexible curb design is essential for such a space to be both permeable and efficient in dealing with evolving demand. Curb data collected in Atlanta, GA showed that pick-up/drop-off activity differs significantly from traditional parking behaviors both in terms of dwell time and event location, and also allowed for a calibration of double-parking behavior. Application of micro simulations models identified that a progressive shift away from traditional long-term parking towards PUDO led to an observed higher curb productivity and lower occupancy. The introduction of dedicated pick-up/drop-off zones at the curb created significant reductions in delay.

Keywords:
shared mobility, VISSIM, travel attitudes

EXECUTIVE SUMMARY

This research assesses people's willingness to share space with strangers and models how design of the physical infrastructure can better facilitate a sharing dynamic. This work contributes to the academic literature associated with attitudes and behaviors of shared mobility by examining the effects resulting from the disruptive event of the COVID-19 pandemic. *Chapter 2* reviews earlier studies on attitudes towards shared mobility and the emerging literature analyzing the impact of COVID-19. The main objective of *Chapter 3* is to report the process and success of different online sample recruitment methods by comparing data quality, cost and efficiency, and characteristics of participants, with the goal of understanding the bias introduced by each method. As web-based surveys become the norm, it is important to continue to analyze the impact of new online survey recruitment methods on data as methodological decisions regarding sample recruitment can have important effects on sample characteristics and study results. The responses resulting from the five recruitment methods in the 2020 GT COVID-19 Mobility Survey (community outreach over email from neighborhood newsletters, social media targeted advertisements, paid opinion panel service, opt-in panel on Mechanical Turk, and opt-in participation collected from past survey efforts), are compared by participation behavior and data quality, cost and efficiency, potential for panel formation, and demographic representativeness.

The study in *Chapter 4* provides important early insights into the attitudes of comfort and usage behavior of shared modes before the pandemic, during a re-opening phase of the pandemic, and the predicted future "when a vaccine is available". This research bridges gaps in knowledge related to COVID-19 and shared mobility so transportation policy and plans can best reflect changes in the "new normal". The study in *Chapter 5* harnesses the longitudinal panel data (Wave 1 and Wave 2) to model the changes in willingness-to-use shared mobility and actual usage of transportation modes during different stages of the COVID-19 pandemic. It explores the reported expectations around the future of transportation during times of uncertainty. The study results can help transport authorities and transit operators return to a 'new normal' in the current crisis and prepare a contingency plan for the next pandemic.

As ride-sharing and ride-hailing services increasingly redefine how people move within urban areas, the curb environment (the public space between roadway and sidewalk) will have to be able to accommodate new uses and new users. *Chapter 6* seeks to understand how formalizing a space for curbside pick-up and drop-off activity typical of new transportation modes such as ride-hailing will impact traffic flow and curb use. By varying traffic flow conditions and changing the percentage of pick-up and drop-off parking events, a comprehensive analysis of different curb configurations was conducted, and results were compared with those from a traditional curb design. With high utilization, dedicate pick-up and drop-off zones have the potential to reduce double parking, increase curb utilization and positively affect through traffic.

1.0. Introduction

Shared mobility can be generally defined as "transportation services and resources that are shared among users, either concurrently or one after another" [1]. Shared transportation options include traditional public transit (e.g. buses, trains, ferries), micromobility (e.g. bike-sharing and scooter-sharing), automobile-based modes (e.g. carsharing, ride-hailing, microtransit), and commute-based modes (e.g. carpooling, vanpooling). Carsharing, bike-sharing, and scooter-sharing allow users to share the *usage* of a transportation mode while ride-hailing, carpooling, and public transit allow users to share a *ride* in a transportation mode. Transportation as a shared resource is an important concept as it can reduce congestion, emissions, and fossil fuel dependency.

Recent innovations in technology communications have resulted in many of these shared mobility services becoming more convenient and accessible. In particular, the use of transportation network company (TNC) platforms, including Uber, Lyft, Didi, and Grab, has exploded across the globe over the past decade; Uber operated in 63 countries and completed 14 million trips each day in 2018 [2]. These platforms operated through smartphone apps, conveniently connected drivers and riders, displayed updated travel time information, and linked to an easy electronic payment. TNCs often described their services as "ride-hailing" and "ride-sharing" but these two terms should not be used interchangeably. Ride-hailing generally describes a peer-to-peer service in which a rider uses an app to contact and pay for a driver to pick them up and take them where they need to go. Examples of ride-hailing services include Uber and Lyft. For a desired trip, TNCs allow users to select from a variety of service options including vehicle size, quality of vehicle, and inclusion of other passengers. Unlike a *private* ride-hailing trip in which a rider hails a driver through an app and travels solo (or with their small party) in a vehicle to a destination, a *shared* ride-hailing trip includes traveling with another passenger(s) (not necessarily in the same party) who was matched because they were traveling in a similar direction. Examples of this subset of ride-hailing services known as *shared* ride-hailing service include Uber Pool and Lyft Line. These services can also be referred to as 'ride-splitting', 'pooled ride-hailing', 'pooled-on demand services', 'shared ride-sourcing', or 'ride-sharing'. Outside of the ride-hailing context, 'ride-sharing' can also be used to broadly include other pooled transportation services like carpooling and public transit.

TNCs claim to be the future of shared and sustainable transportation; the flexibility associated with ride-hailing services has resulted in some users being less likely to own a car and complementing their ride-hailing use with transit for longer trips [3]. On the other hand, the use of ride-hailing may result in increased vehicle miles traveled because of empty vehicle miles, induced trips, and modal shifts from public transit and active modes [4]. The large majority of Uber and Lyft rides only serve one user and therefore take up the same space (or more) as typical cars [5,6]. Ride-hailing may allow people to live a car-free lifestyle but the concept of every rider in a separate private vehicle will ultimately add to traffic congestion.

Research has shown that although the majority of urban rides could be shared with minimal extra time disutility [7,8]. only a small percentage (around 20%) of ride-hailing rides were selected to be shared [9]. Even if a user selected the shared ride-hail option, if there aren't enough other shared ride-hailing users headed in the same direction, the most efficient route may not be a shared ride. Pooled ride-hailing has the potential to bring large benefits to urban areas only if it replaces at least half of solo ride-hailing rides [10]. For a more efficient use of the roadway, policymakers must encourage a shift in travel from solo ride-hailing toward shared ride-hailing.

In March 2020, the novel coronavirus (COVID-19) pandemic dramatically impacted the way people around the world lived, worked, and used transportation. The virus responsible for COVID-19, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), moved through respiratory droplets and was most commonly spread between people who were in close contact with one another [11]. Additionally, during the first few months of the pandemic, there was an exaggerated emphasis placed on the transmission of COVID-19 through infected surfaces. To reduce potential exposure, individuals around the world chose to work from home, only leave home for essential trips, increase sanitation measures, and travel with as little contact with strangers as possible. In addition to personal decisions to reduce contact, governments around the world enacted different restrictive guidelines, including stay-at-home orders and required social distancing. After the initial disruption from COVID-19 in mid-2020, distancing restrictions were slowly lifted in response to social and political pressures sometimes only loosely connected (if at all) to declines in infections and deaths. Although COVID-19 vaccines became available starting mid-December 2020 in the US and there was wide-spread access and interest in the vaccines in the US throughout 2021, COVID-19 cases continued to emerge in 2022. Health experts suggested preparing for a "next normal" or "new normal" scenario where we live with COVID as an endemic instead of a pandemic disease [12]. "New normal" scenarios mean the COVID-19 virus will be a constant threat that will need to be managed. Looking to the "post"-COVID future, the public may never fully return to their pre-COVID behaviors and attitudes.

As the US government's COVID-19 public health emergency was extended to at least mid-July 2022, understanding the impact of COVID's ongoing threat on shared mobility was important to building a well-planned and resilient transportation system. Reaction to the pandemic varied among different states and populations. While some states (e.g. California and New York) were reluctant to ease COVID restrictions, others (e.g. Georgia and Florida) were quicker to ease restrictions and reach a "next normal" scenario. The city of Atlanta, GA served as an interesting example of an urban area with COVID restrictions that were eased quicker than other urban areas. The number of positive

COVID-19 cases in metro Atlanta, GA fluctuated in the almost two-year period since the start of the pandemic, as seen in Figure 1-1. In Atlanta, four "peaks" of positive COVID cases occurred: in the early summer of 2020, late fall 2020 / early winter 2021, late summer of 2021, and early winter of 2022. Despite the unsettled infectious landscape, the state of Georgia slowly phased out pandemic-related policies; the stay-at-home order expired on April 30, 2020, the social distancing requirement ended in May 2021, and the statewide COVID-19 emergency order ended in July 2021. Most of Georgia's COVID-19 protocols were lifted by 2022 (Atlanta's indoor mask mandate ended at the end of February 2022) as vaccines were widely available (as of December 2021, at least half of the Georgia population was fully vaccinated).

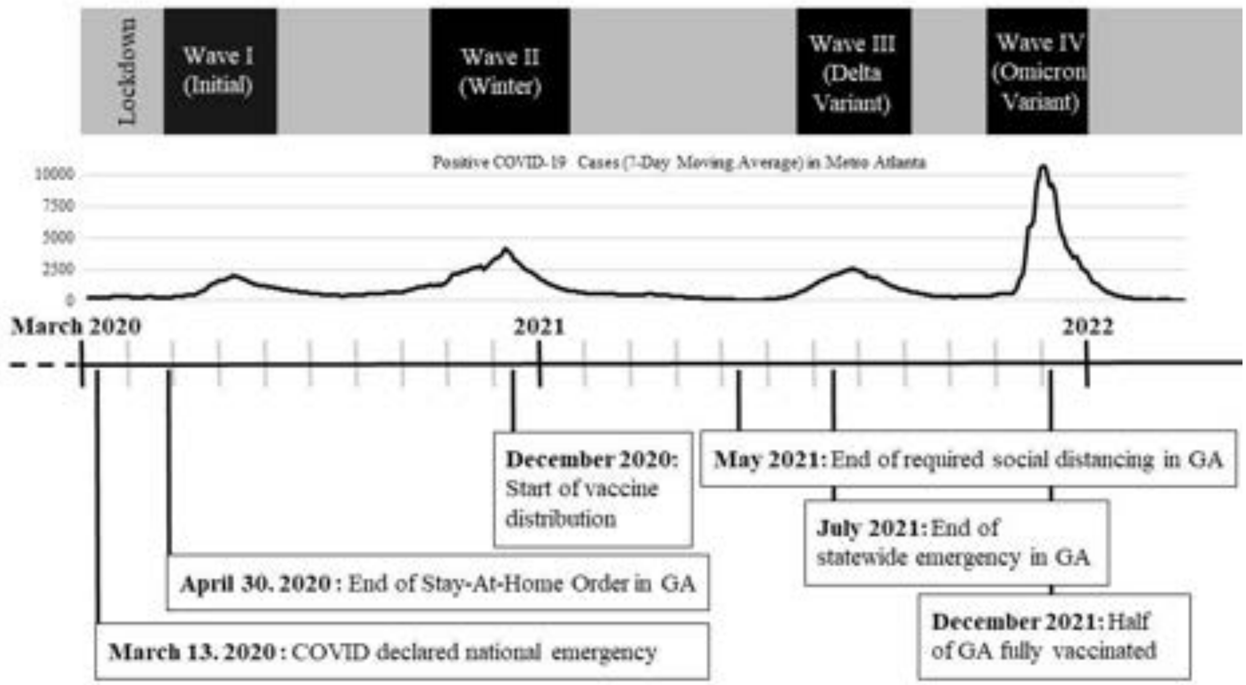


FIGURE 1-1: TIMELINE OF COVID-19 CASES AND POLICIES IN GEORGIA

Pandemic-related policies for shared mobility as well as shifting attitudes and activity patterns from the pandemic impacted many transportation options as they were considered unsafe or unavailable. Transportation modes utilizing a shared nature significantly decreased in usage as the risks associated with COVID-19 reduced peoples' willingness to share space [13,14]. Micro-mobility e-scooter services, including Bird and Uber's JUMP, were initially suspended for a few months (April to July 2020). Public transit temporarily reduced service from March 2020 until late 2020, and when it returned, required passengers to wear masks until April 2022. Shared ride-hailing services including UberPool and Lyft Shared, were suspended for a longer period starting March 17, 2020. In March and April 2020, TNC's encouraged the use of ride-hailing services for only essential trips. In May 2020, Uber and Lyft outlined measures and precautions for ride-hailing services including passenger limits, face mask requirements for drivers and passengers, a requirement for passengers to ride in the back seat, encouraging air circulation with rolled down windows, and a vehicle cleaning guide. As the pandemic continued, ride-hailing services increased efforts to reduce risk by introducing contact tracing and distributing mask and sanitizing products. After vaccines became widely distributed and distancing restrictions were loosened across the US, some shared ride-hailing services returned in select cities in 2021; Lyft shared rides returned mid-July 2021 (Philadelphia, Chicago, and Denver) and May 2022 (San Francisco, San Jose, Denver, Las Vegas, and Atlanta) while UberX Share rides returned November 2021 (Miami) and June 2022 (New York City, Los Angeles, Chicago, San Francisco, Phoenix, San Diego, Portland, Indianapolis and Pittsburgh) [15]. The return of shared ride-hailing services included new restrictions including a limit of two people per pooled rides and no sitting in the front seat.

The COVID-19 disruption dramatically impacted mobility, especially shared modes such as ride-hailing, shared ride-hailing, and public transit, and presented a unique opportunity to study attitudes, reactionary behavior, and recovery. A disruption with the magnitude of the COVID-19 pandemic had the potential to bring about many short-term and long-term behavioral changes. To predict if the "social distancing" nature and resulting shifts in behavior from the pandemic continued to persist after the pandemic ends, this work examined preferences and behaviors towards shared mobility during different stages of the pandemic. Understanding the impact and response from this disruption was important to aid policymakers in building a more resilient and sustainable transportation system.

1.1. Scope

In order to gain insight on attitudes during times of uncertainty, predict longer-term impacts from the disruptive event of COVID-19, and work towards an environment that facilitates and encourages sharing vehicles, this work examines and utilizes online surveys regarding shared mobility throughout the COVID-19 pandemic in *Chapters 3, 4, and 5*. A two-wave online reported and revealed preference survey was implemented to measure the comfort and usage of users on three types of shared mobility: (1) private ride-hailing, (2) shared ride-hailing, and (3) public transit, during three time periods: (1) recent past, (2) current, and (3) future. The Wave 1 COVID-19 and Shared Mobility Survey, available in Appendix D, was distributed during October 2020 and targeted adults in the Atlanta, GA area. The Wave 2 COVID-19 and Shared Mobility Survey, available in Appendix E, was similar to the first wave survey with updated timelines and distributed during October 2021. In *Chapter 6*, a series of microscopic simulation models calibrated using data collected in Atlanta, GA, were devised, and performance metrics such as delay and occupancy rate were collected.

2.0. Literature Review

The following extended literature review includes related topics that are referenced throughout this report. This chapter serves as an introduction to the impact of attitudes and behaviors in shared mobility and the emerging COVID-19 literature.

2.1. Self-Reported Attitudes and Behaviors

The mechanisms behind shifting mobility patterns can be explored through the lens of attitudes and behavior. The complex relationships between attitudes and travel behavior has been examined extensively in the literature as attitude, desired use, intention, behavior, and satisfaction of a mode choice are all linked [1,2]. Attitudes influence preferences, the desired mode use of one alternative over the other, which influence mode choice and behavior. This actual behavior is often captured by the amount of usage of a mode. Understanding mode attitudes, i.e. the perceptions of travel mode characteristics as well as the liking for various modes, is especially important when actual behavior cannot be observed. Travel mode attitudes are traditionally evaluated in surveys through Likert-style questions. The preferred mode isn't always chosen by an individual, so it is important to examine both reported and revealed preferences to understand intended and actual behavior.

Relying on self-reported measures for attitudes and behavior introduces potential bias. People tend to exaggerate the degree to which their future tastes will resemble their current tastes. This projection bias means people usually expect that they will be more satisfied with their future lives [3]. During the COVID-19 pandemic, this unrealistic optimism bias was especially prevalent as the pandemic ushered in a period of uncertainty. After multiple strains and waves of the new virus, the future may have felt hard to predict. During the pandemic, some individuals were more inclined to have hope for the future while others predicted a future filled with losses [4]. The assessed risk of infection varied by the individual and impacted the likelihood of engaging in protective behavior [5]. Asking respondents to forecast attitudes during times of uncertainty introduces new challenges to understanding transportation attitudes and behavior.

2.2. Attitudes on Shared Ride-Hailing

The inclusion of ride-hailing services in forecasting transportation attitudes and behaviors is recent research trend as private ride-hailing was first introduced in 2010 and shared ride-hailing services first became available in a handful of major US cities starting with San Francisco in 2014. The growth of shared ride-hailing was more limited than the growth of private ride-hailing; as of 2019 Uber Pool was available in more than 50 cities while Uber was available in more than 10,000 cities around the world [6]. Shared ride-hailing services were introduced in the primary area of this study, Atlanta, in 2015.

Unlike public transit which offered a mostly uniform and expected experience (e.g. bus or rail on a fixed route or schedule), shared ride-hailing experiences varied depending on the ride, city, and option selected. Variations of the typical shared ride-hail service included “Non-Stop Shared Ride” where a rider is guaranteed to get dropped off first in their pooled ride [6], “Pool Chance Ride” where a rider has the chance of getting a discounted ride if the driver picks up other riders and otherwise pays the individual ride fees, “Uber Express Pool” where instead of door-to-door pooled service riders are picked-up or dropped-off at a spot close to their destination, and “UberHOP” where a rider meets at a pickup location at their requested departure time, joins a designated commute route with up to five other passengers, and exits at a group drop-off location [7]. To add to the confusing amount of TNC sharing options, Uber Pool recently became known as UberX Share and Lyft Shared was previously introduced as Lyft Line.

Although shared ride-hailing services have only been available for a short period of time, some users have embraced pooled rides due to their economic, social, and environmental benefits. A number of socio-demographic variables have been associated with shared ride-hailing users including educated individuals who currently work or work and study [8], generally younger individuals [8-10], individuals with lower incomes [11], and individuals who live in metro areas [9]. Riders' desire for personal space, a dislike of social situations, a distrust of others, and concerns about security and privacy limited the usage of shared ride-hailing [12-14]. When compared to the extensive literature on private ride-hailing [15], a more limited number of research studies distinguished the characteristics and adoption of shared ride-hailing.

To examine individuals willing to use shared ride-hailing services, a number of studies have associated a monetary value with different ride-hailing situations. These studies found that an individual's willingness to pay was significantly less for a shared than a solo ride-hail and changed depending on the number of additional passengers and time added to the trip [16]. The willingness to pay for a shared ride-hail also depended on the type and length of the trip - a commuter rider was less willing to pay than a leisure rider [17,18] and longer rides would require greater discounts [16]. Increased travel time and the presence of another person in the vehicle were the two most important factors that decrease the likelihood of adoption of shared ride-hailing compared to private ride-hailing [8,10,19]. Recently, a model for the choice between pooled and private ride-hailing, a generalized heterogeneous data model (GHDM), integrated psycho-social latent constructs (e.g. tech-savviness, sharing propensity, and green lifestyle propensity), demographics, and pooled ride-hailing familiarity, and found that higher levels of tech-savviness were associated with higher private (not pooled) ride-hailing propensity and people who have a high sharing and green lifestyle propensity were more likely to use shared ride-hailing [20].

Existing literature has modeled the trade-offs between pooled and private ride-hailing but transit may have served as a closer substitute to shared ride-hailing than solo ride-hailing [21,22]. Just as in shared ride-hailing, high cost and long trip duration were significant factors for transit mode choice. The relationship between transit and shared ride-hailing was complex, with some studies finding the modes to be complementary [23] and some competitive [24] depending on the transit mode (bus vs commuter rail vs subway) and quality of service [25]. Comfort was an important aspect of the transit passenger experience and was similarly important in pooled ride-hailing.

2.3. COVID-19 and Shared Mobility

The COVID-19 pandemic resulted in dramatic shifts in perceived comfort and use of transportation services. A growing number of studies examined the impact of COVID-19 on transportation behaviors during the pandemic. During the early months of the pandemic, March and April 2020, the number of trips for all modes significantly dropped [26,27]. This dramatic shift in transportation demand was driven by changes in activity and attitudes as non-essential activities were discouraged, remote work was embraced, and the risks associated with sharing spaces were re-evaluated. Ridership of transit, ride-hailing, and shared ride-hailing decreased and customer attitudes indicated a significant drop in usage of public transit and ridesharing apps and services [18]. These early trends and predictions motivated further research into the potential long-term impacts on behaviors and transportation preferences from the pandemic.

As the pandemic continued into the summer of 2020, two research studies examined the current and future impact of COVID-19 on transportation behavior by collecting survey data across the U.S from April to June [28,29]. These studies captured an increase in work-from-home activities and a shift away from shared mobility options. While the majority of survey respondents expected their use of various modes in the "new normal" to return to levels before the pandemic, a significant minority expected a change likely due to new work-from-home options and public transit may not fully recover to pre-pandemic ridership levels [28]. The decrease in usage of transit, shared ride-hailing, and private ride-hailing use during the pandemic was likely due to the highest perceived risk from these travel modes [29]. In a survey collection effort that occurred in July and August 2020 [30], a large majority of respondents (more than 60%) expressed some skepticism in their use of shared transportation modes such as public transit, shared ride-hailing, and private ride-hailing during the pandemic. Shared modes, like transit and pooled ride-sharing, were associated with high exposure risks [31,32]. This trend of skepticism in shared mobility was predicted to continue even once the COVID-19 pandemic was no longer a threat.

Over the two years since the start of the pandemic, several studies have attempted to understand the impact of the pandemic on shared mobility forms. One study involved a web-based survey, recruited through a market research company survey, distributed to

Greater Toronto Area (GTA) residents to examine the stated preferences and impacts that the pandemic had on different aspects of their use of private and pooled ride-hailing in the pre-COVID period, COVID recovery period of July 2020, and the post-COVID period [31]. This data estimated a two-stage ordered logit models of the earliest stage post-COVID at which a person would consider using private and shared ride-sourcing. It found that usage of private ride-hailing would gradually increase with lifted restrictions, but levels of usage were unlikely to fully return to pre-pandemic levels until COVID-19 was no longer considered a threat.

The understanding of risk surrounding the COVID-19 pandemic has shifted to involve a “New normal”, meaning the COVID-19 virus will be a continue to be a threat seasonally. Additional research is required to evaluate the long-term impacts of the pandemic on ride-sharing attitude and utilization.

3.0. Comparison of Online Survey Recruitment Methods: Differences in Respondent Demographics and Attitudes

3.1. Introduction

Traditional mode choice and attitudinal surveys were historically conducted through the use of postal questionnaires or phone interviews. Over the last twenty years, these surveys have migrated from paper to online portals due to shifting technologies of the internet and mobile devices. Today, online surveys have developed into an entire industry in market research and are commonly used in academic research. Although web surveys have a lower response rate than mail-back surveys, their low-cost and time efficiency allow them to recruit a large sample therefore proving to be a promising mode for survey research [1]. Additionally, web-based surveys can mitigate some negative biases present in other survey forms such as interviewer effects in phone and in-person interviews [2]. Although web-based surveys offer an effective and lower-cost alternative to traditional methods, online surveys often rely on non-probability and convenience sampling techniques to recruit respondents [3].

The non-random nature of web-based survey recruitment can result in coverage error, low response rates, and non-response error [2,4-5]. Online convenience sampling techniques can over- and under-represent certain categories of age, income, gender, and other demographic variables. Demographic differences in non-random web-based surveys can be partially explained through topical self-selection (a higher response rate of people who were more interested in the topic) and economic-based self-selection (a higher response rate of people who were interested in the survey for the monetary incentive) [6]. Although poor quality data resulting from this self-selection can (and should) be cleaned from the analysis, it can still impact the research results. Data with a high proportion of incomplete responses, high speed through the survey, unrealistic and inconsistent answers, and nonsensical responses point to a larger issue with the data set. While non-probability convenience samples are acceptable for modeling relationships, they are not ideal for descriptive analysis and conclusions [7]. Because the motivations and other unobserved traits of people who join web panels are systematically different, weighting schemes based primarily on demographics may not be enough to overcome the self-selection biases arising from coverage and non-response errors [8]. As survey recruitment methodology impacts the collected respondents' attributes and data quality, it is important that researchers make thoughtful decisions when developing, implementing, and analyzing findings from different survey sample recruitment techniques.

A variety of studies in medical, political, and social sciences have examined and compared costs, data quality, and population representativeness from multiple online recruitment methods. These studies and more have found that the participation rates of people of different ages, incomes, genders, and other demographic variables vary by survey recruitment methods [3, 9-12]. While MTurk offers the cheapest and fastest recruitment, Qualtrics Panel was the most demographically and politically representative [4]. Data quality between crowdsourced (MTurk, CloudResearch, Prolific) and commercial panel (Qualtrics, Dynata) samples [13]. Each sample differed in comprehension and attention, with Prolific and CloudResearch performing the best. Outside of some recent survey methodology papers, scholars rarely compare sources of online respondents to one another and do not clearly state if they considered alternative methods during the survey design stage.

More limited literature regarding respondent attributes and online survey recruitment methods exists in transportation research. In 2015, Hoffer compared stated preference questionnaires on walkability through MTurk, commercial panel, and conveniently recruited samples and found the commercial panel to be the most diverse and highest quality [14]. It was concluded that convenient, viral distribution should be avoided because of social clustering concerns. In 2019, Gaupp-Berghausen et al. examined active transportation usage in select European cities through a mixed recruitment approach including Facebook, mailing lists, flyers, poster, radio, collaboration with local administrations and organizations, and street recruitment [6]. The effectiveness, time-efficiency, and representativeness of each recruitment strategy for each city was expanded, finding social media to be the most effective. Zhang et al. (2020) surveyed individuals' vehicle ownership and transit usage during the pandemic by recruiting participants through Facebook ads and the Transit app. While the Facebook approach recruited more female participants, the Transit app recruited greater participation from younger riders and lower-income riders [15]. In 2020 Silvano et al. compared three different recruitment methods (sampling from a population register, web-panel, and crowdsourced) and found the recruited participants from crowdsourcing differed the most from registered demographic data [16]. Recently, Wang et al. (2022) compared five cross-sectional travel surveys, each with different sampling methods, and found the online opinion panel resulted in the highest response rate [17]. Interestingly, respondents recruited via online opinion panels reported lower life satisfaction than those recruited by other methods, which indicates that the online opinion panel members may not be representative of the general population's demographics or attitudes.

The novel coronavirus (COVID-19) pandemic dramatically impacted the way people use transportation; attitudes and activity patterns changed overnight as many transportation options were considered unsafe or unavailable after the COVID-19 pandemic was declared a national emergency in the U.S. on March 13, 2020. A number of researchers across the globe quickly deployed online surveys to capture changes in travel behavior and gain insight on the impacts of COVID-19 on transportation. With the possibility of infection preventing in-person recruitment, slow response time and costs related to mail recruitment, and low response rate of phone surveys, many traditional random methods of sampling were impossible or inefficient for capturing attitudes and behaviors during the dynamic situation surrounding the pandemic. The internet offered a solution to rapid survey deployment with a plethora of convenient sampling methods and platforms for the deployment of online questionnaires.

The transportation research community quickly responded to the pandemic by deploying a large number of online surveys. A brief literature review of published journal papers in the Transportation Research International Documentation (TRID) database containing the keywords “COVID-19” and “Travel Behavior Surveys”' was conducted in June and July of 2021 and resulted in 29 publications that were reviewed, and the methodology analyzed, as displayed in Appendix C. Convenience sampling methodology and an online survey mode were used in all examined journal papers while only two papers indicated the use of a survey mode in addition to an online survey: with one using direct mail [18] and the other telephone [19]. Half (n=15) of the examined papers used multiple recruitment methods with the most prevalent recruitment method involving paid panel survey companies (n=14) and distribution through social media platforms (n=12). Two papers did not clearly indicate any online survey recruitment methodology [20-21]. In the analysis of the survey results, eleven (n=11) papers did not discuss the limitations of recruitment methodology or implications of the sample characteristics on the resulting analysis. Scholars infrequently compare sources of online respondents to one another and are often not clear if they considered sampling alternatives during the design stage. These findings highlight the need for more extensive reporting of survey recruitment methods and deeper analysis before generalizing and interpreting results.

To investigate the different costs and potential bias resulting from web surveying methodologies, this study distributed an online attitudinal survey regarding mobility during the COVID-19 pandemic through multiple methods in the Atlanta metro area. This paper describes the process and outcomes of these different online survey deployment and recruitment methods with the goal of understanding the advantages and disadvantages introduced by each method (Qualtrics paid panel, Mechanical Turk (MTurk), Facebook advertisements, NextDoor posts, Email newsletters, and pre-recruited from past surveys). The primary purpose of this study is to add to the knowledge base regarding the use of online survey recruitment techniques as a viable means of collecting data for transportation research, specifically on shared mobility. This paper reports the limitations and success of these different recruitment methods with regard to obtaining participants’ characteristics, participation behavior, recruitment rates, and representativeness of the sample. This study is the first transportation panel survey effort to compare the recruitment methods from five different sources, namely MTurk, Facebook advertisements, paid commercial panel members, convenience neighborhood mailing lists, and email lists from past survey efforts.

3.2. Methodology

A Wave 1 online survey hosted on the Qualtrics platform was implemented on October 14, 2020 and concluded on November 18, 2020. This data collection period was selected due to the relative stability of virus cases; during the data collection time, the Atlanta metro area had a slight increase in new COVID-19 cases but no change in restrictions or major change to the development of vaccines [22]. Qualtrics online questionnaires were collected through multiple online recruitment channels to sample the population of adults in the Atlanta metro area. Each recruitment channel had a personal survey link to track the recruitment method for each respondent. The main questionnaire text was the same for all recruitment channels. A minor change was be included in the Qualtrics and MTurk questionnaire, which both omitted an optional question asking for respondents' email if they would like to be contacted for future studies, as this was not allowed by these survey platforms.

3.2.1. Questionnaire Development

To assess the reported and revealed preferences of transportation users in the Atlanta area, the brief online survey was designed and developed to be completed in 10 minutes or less with five short sections. The length of the survey was mindful of participant time as length of a survey has a negative effect on the response rate but no significant effect on the accuracy rate [23]. The survey was published on a user-friendly survey platform, Qualtrics, with a simple survey design. To establish trust with the respondent, branding of survey and survey recruitment materials included official university logos and names of research professionals [1].

Following an informed consent form, the first set of questions collected participants' level of comfort on different shared modes during three time periods: the period before COVID-19, the current time when they completed the survey, and a future period when a COVID-19 vaccine is available. A definition of each shared mode was included in this section to familiarize participants with terms used in the survey. After indicating their level of comfort on a Likert-scale, the survey included a series of Likert-scale general attitude statements and opinion statements related to existing COVID-19 procedures in transit and ride-hailing. The third and fourth sections were designed to collect frequencies of trip usage for different modes in a typical time before the COVID-19 pandemic and in the past month during the COVID-19 pandemic. The fourth section included an attention check which flagged invalid responses from the data set based on knowledge that shared ride-hailing services were suspended during the pandemic. Therefore, if a respondent indicated that they have used shared ride-hailing services in the past month during the pandemic, they were flagged as poor-quality data. The survey concluded with common demographic questions to collect background information about each respondent including age, race, gender, education, income, and employment status. The completion of all questions was required for participants to continue in the survey, except for four open-ended questions where respondents had the opportunity to further explain their selected answers, as displayed in Table 3-1.

The survey included questions regarding both revealed preferences and reported preferences. Revealed questions characterized individuals' existing sociodemographic and mobility behavior. This included monthly frequency for ten transport modes and four trip-replacing technologies before and during (October 2020) COVID-19. Reported preferences questions predicted changes in mobility behavior by collecting respondents' opinions and attitudes towards some potential scenarios and statements. These questions were necessary as not all forms of shared mobility were available during the pandemic and reported preference data could only report actual alternatives. Reported preference questions captured the hypothetical level of comfort using shared mobility (specifically private ride-hailing, shared ride-hailing, and public transit) during different stages of the pandemic and with various COVID-19 regulations questions. The goal of these questions was to capture individuals' potential acceptance of shared mobility measures during the pandemic and its impacts on their willingness to share mobility.

TABLE 3-1: WAVE-1 SURVEY CONTENT

ID	Question Type	Description
1	Matrix table with 3 statements and 5 scale points	Comfort using mobility before COVID-19 *
2	Matrix table with 3 statements and 5 scale points	Comfort using mobility current COVID-19 risk *
3	Matrix table with 3 statements and 5 scale points	Comfort using mobility when a COVID-19 vaccine is available *
4	Matrix table with 8 statements and 5 scale points	General attitudes and preferences *
5	Matrix table with 6 statements and 5 scale points	Public transit and COVID preferences *
6	Matrix table with 6 statements and 5 scale points	Ride-hailing and COVID preferences *
7	Text entry	Ride-hailing and COVID additional thoughts
8	Matrix table with 10 statements and 6 scale points	Frequency of modal usage before COVID-19 *
9	Matrix table with 4 statements and 6 scale points	Frequency of technology usage before COVID-19 *
10	Matrix table with 10 statements and 6 scale points	Frequency of modal usage current COVID-19 risk *
11	Matrix table with 4 statements and 6 scale points	Frequency of technology usage instead of a trip *current risk* *
12	Matrix table with 4 statements and 5 scale points	Attitudes and preferences on activities during COVID *
13	Multiple choice with 2 choices	Public transit service suspension impact (Y/N) *

TABLE 3-2: CONTINUED		
ID	**Question Type**	**Description**
14	Multiple choice with 2 choices	Shared ride-hailing service suspension impact (Y/N) *
15	Text entry	Additional thoughts on transportation and COVID
13b	Multiple choice with 2 choices	Change in public transit service
13c	Text choice	Public transit and COVID additional thoughts
16	Text entry	Birth year *
17	Multiple choice with 6 choices	Educational background *
18	Multiple choice with 3 choices	Gender identity (M/F/S) *
19	Multiple choice with 2 options	Hispanic (Y/N) *
20	Multiple choice with 5 options	Race (multiple answer choices) *
21	Text entry	Zip code *
22	Multiple choice with 7 options	Employment situation before COVID (multiple answer choices) *
23	Multiple choice with 7 options	Employment situation current (multiple answer choices) *
24	Multiple choice with 6 choices	2019 Household income *
25	Text entry	Email
26	Text entry	Additional thoughts on topic or survey

* Indicates required response

3.2.2. Recruitment Methods

The target population for the study comprised adults in the Atlanta-metro area. In this study, six recruitment methodologies were investigated for potential use resulting in the use of five distinct recruitment sources for this survey effort. These methodologies include (1) inviting respondents from previous surveys who opted in to participation in future surveys, (2) community outreach over email list from neighborhood newsletters, (3) social media targeted advertisements, (4) paid opinion panel service, (5) opt-in panel on Mechanical Turk (MTurk), and (6) and paid Google Consumer Survey sample. Online recruitment methods were categorized as either "pull-in", where an online user was actively looking for paid work through a survey, or "push out", where an online user wasn't seeking work and needed to be engaged with the use of an ad, email request, or incentive [3]. Although only six recruitment methodologies were actively pursued for this study, there exists a large variety of online survey recruitment methods utilized by transportation researchers including crowdsourcing (Prolific, CrowdFlower) and commercial panel services (PureProfile, Knowledge Panel, Cross Marketing, Survey Monkey, Harris Poll Online, Kantar, Prime Panels). Each of the selected recruitment methods are explained further below:

1. Opt-in Participation from Past Survey Efforts (Email Recontact): In prior research surveys, some participants indicated that they might be willing to respond to future surveys by sharing their recontact information. Recontact information was used by researchers to ‘push out’ a survey notification to previously willing respondents. Participants may have experienced survey fatigue and stopped responding to surveys, resulting in non-response bias; prior studies have found that panel members and non-response members differed significantly in terms of the need for recognition, absorption, extraversion, and agreeableness [8].

In this survey effort, recontact information was collected during an intercept survey of MARTA riders after the I-85 road closure in 2017 (262 email addresses collected) (French et al., 2019) and a mailed survey on bicyclist preferences that targeted populations in the Westside, Eastside, Grant Park, and South Atlanta neighborhoods near the Beltline in 2017 and 2019 (1185 email addresses collected) [24].

The two prior survey efforts resulted in the collection of 1447 emails from the Atlanta population. Each prior participant was invited to the present survey through a single email request with university branding and a link to the Qualtrics portal. No reminder email was sent to request a response if they did not reply to the first email. No monetary incentive was given to participants to complete the survey.

2. Community Outreach: For location-targeted sampling, collaboration with local administration or organizations can be productive and convenient for reaching the general local population. This method can collect a relatively representative sample but dramatically depends on local administration effort [6]. This method behaves like a “push out” recruiting flow.
This study reached out to 58 neighborhood planning units and neighborhood organizations in the metro-Atlanta area as identified by the City of Atlanta neighborhood organization directory. The emailed request asked local organizations to share the questionnaire link with a description and recruitment photo in their newsletter, website, or social media. A follow-up request was sent a week later to the organizations that did not respond. Only 17 organizations (29%) agreed to share the survey within their community through online newsletters, email groups, and/or social media like Facebook and Nextdoor. These agreements were not verified. Four organizations were not willing or able to share the survey with their community within a timely manner. The other 37 local organizations did not respond to the survey push request; this may be due to incorrect or out-of-date contact information. No incentive was given to participants or organizations who shared the survey. Participants who were recruited through this method were linked directly to the Qualtrics survey page and were not provided with any monetary compensation.

3. Facebook Advertisements: Social media recruitment for surveys has been embraced by the social, health, and education fields. Formal advertisement-based social media recruitment campaigns commonly utilize Facebook due to its popularity among users. These studies have found that Facebook advertisements tend to over-recruit younger women [15,25-26] and did not reach the digitally disconnected. To minimize these concerns, Facebook advertisements can target populations to increase the representativeness of the sample [27]. This method has been successfully used for better access to hard-to-reach populations [28-30]. Advertisements can be targeted to specific audiences based on location, age, gender, language, connections, interests, and behaviors, for no or limited additional costs. Ads are displayed based on a paid bid system by number of clicks, ad views, or action taken at a website. Facebook advertisements offer a variety of options for the ad campaign including placement options, where to drive traffic, budget and scheduling options, ad setup, and more. Ads must be attractive as this method behaves like a 'push out' recruiting flow. There is no built-in incentive procedure for survey completion through the Facebook advertisements.

For this study, a Facebook advertising campaign was implemented with the objective to generate traffic by linking directly to the survey website. The campaign ran during the full data collection period. The targeted audience for the ad was adults (18+) located in the Atlanta area. The campaign, which included visual media ad and call-to-action text linking directly to the survey site as seen in Figure 3-1 was set to spend $50 a day. The placement of ads was automatically selected through Facebook's delivery system. The media used in the advertisement evoked a visual brand related to Georgia Tech's visual identity. The visual ad contained call-to-action text for respondents to complete the survey, but no incentive was offered to participants in the advertisement. Facebook previously rejected ads with more than 20% text-to-image ratio, but this barrier of usage was removed in 2020. The ad image was designed to minimize the amount of text as images with less text perform better. Respondents who viewed the ad had to self-select into the study, by clicking "Learn More", and then completing the survey linked to the external Qualtrics page.

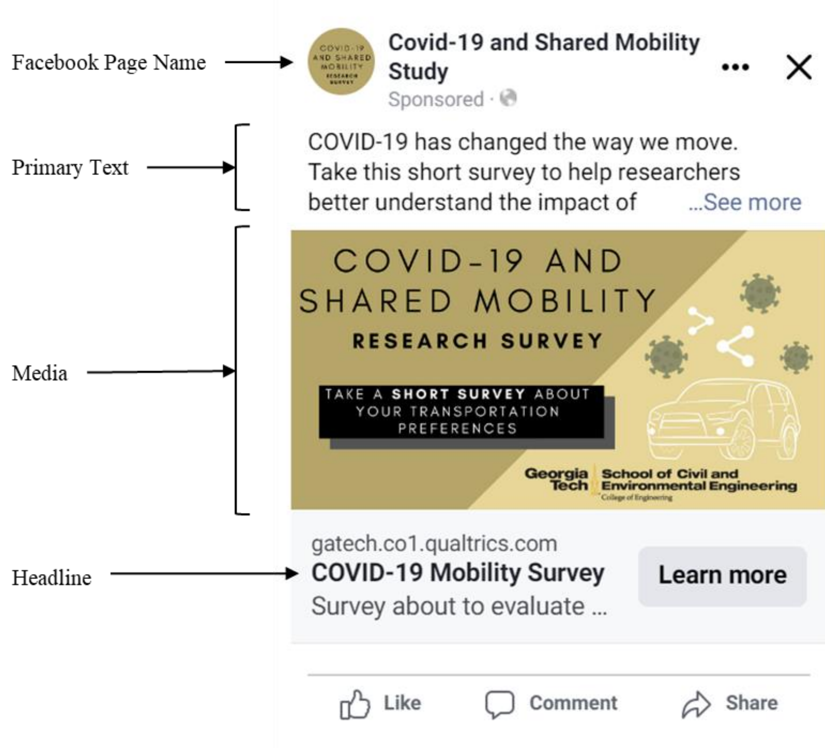


FIGURE 3-1: FACEBOOK ADVERTISEMENT FOR STUDY

4. Opt-in Panel Mechanical Turk: A large body of literature has evaluated Mechanical Turk (MTurk) samples in the United States through the lens of different disciplines. MTurk is a task distribution platform where requesters post simple paid tasks (Human Intelligence Tasks aka HITs) such as surveys, to recruit respondents who are actively looking for employment (a 'pull in' recruitment flow). Requesters post HIT announcements with an estimated completion time and compensation. For survey-related tasks, if respondents select the HIT, they are redirected to the external Qualtrics site to complete the survey. To allows requesters to only reward quality respondents, the end of the linked survey can ask for an MTurk Worker ID and/or a randomly generated code that is entered into the MTurk HIT system can be displayed on the last page. Although the incentive for each HIT is determined by the requester, it is common practice to reward participants at least the federal minimum wage per hour. In addition to the incentive cost, each HIT costs a 20% fee on the reward. This means MTurk can has the potential to be a cheap and fast recruitment methodology depending on the research purpose and study population [4]. MTurk also has the ability to target specific populations through their qualification and worker requirements. System qualifications including HIT approval rate, location, and number of HITs approved and custom qualifications incur no additional fees per respondent. Respondents with MTurk Masters Qualification can be selected require to high performance across previous tasks resulting in better data quality. These and other premium qualifications target specific socio-demographics like age, industry, language, education and more, incur an additional fee depending on the qualification and quantity.

For this study, the survey task HIT was published twelve times over the data collection period. To participate in the survey task and receive $2 incentive upon completion, MTurk registered workers were required to live in Georgia, have a HIT approval rate (%) greater than 90, and meet the custom qualification of correctly answering a screener question that specified they live or work in the Atlanta area. The custom qualification was created through the use of the MTurk web API. Workers were not required to be Masters to complete the HIT. Keywords to help workers search and identify the tasks included "survey, transportation, Georgia, short, Atlanta". The HIT description for MTurk was the same call-to-action text used in the Facebook advertisement; "COVID-19 has changed the way we move. Take this short survey to help researchers better understand the impact of COVID-19 on transportation service". The HIT design layout used the standard Survey Link project template in the MTurk UI.

5. O*nline Opinion Panel Service (Qualtrics Panel):* Instead of a researcher reaching out directly to survey participants, an online recruitment commercial panel service can be used as an intermediary. These companies have created a pool of prospective participants and 'pulls in' qualified participants based on the researcher's requirements. Panel service companies track the recruitment and data collection process, manage incentives and compensation, and check on data quality by verifying identities and excluding missing or invalid data [31].

In this study, a commercial online opinion panel, Qualtrics Panel, was used to recruit and verify a specific number of guaranteed and timely responses. Each response costs a set rate, but researchers are only charged for complete and quality survey responses (scanned for gibberish and trap questions). Qualtrics Panel is a subdivision of Qualtrics that provides a project manager to monitor and implement each survey according to the researchers needs. Participants were recruited from various sources, including website intercept recruitment, member referrals, targeted email lists, gaming sites, customer loyalty web portals, permission-based networks, and social media, etc. Qualtrics sent an email invitation or prompted on the respective survey platform to proceed with a given survey. Although Qualtrics Panel has the ability to meet specified demographic quotas or target ranges, this study did not impose any quotas. Qualtrics Panel controlled the amount of compensation offered to participants but declined to share compensation details.

6. Google Surveys (formerly Google Customer Surveys): Google Surveys was examined as it is a relatively new tool for survey recruitment. The methodology for recruitment works similarly to an intercept survey; as individuals browse the internet, they may be confronted with a "survey wall" and asked to answer a few questions to access the web content for free. A maximum of ten questions can be asked. The cost structure depends on the number of questions in the survey and targeting requirements; a single question survey can cost as little as 10 cents while a 10-question survey can cost $10. This low-cost for short surveys does limit the survey design flexibility [32]. Google Survey can target postal codes for Android-smartphone users, age, gender, or location. Limitations to this method also include inability to ask about names, phone numbers, email address, and other personal-identifiable information which limits the ability to contact respondents again. Due to privacy and IRB concerns with Google's ownership of the data, as university researchers, this study was unable to use this recruitment methodology.

3.2.3. Second-Wave Survey Recruitment

A Wave 2 survey was distributed a year after the Wave 1 survey to an email addresses distribution list comprising 278 Wave 1 participants that indicated they would be interested in completing future surveys. The second wave survey content was very similar to the initial survey content with only minor modifications including updating the time frame of questions and adding/removing statements to reflect current pandemic conditions, as summarized in Table 3-2. There was no monetary incentive for participants to complete either survey. Unfinished respondents were sent three reminder emails to continue their participation on Tuesday October 12th, Monday 18th, and Friday 22nd, 2021.

TABLE 3-3: WAVE 2 SURVEY CONTENT

ID	Question Type	Description		Wave 1?
1	Matrix table with 3 statements and 5 scale points	Comfort using mobility over the summer in 2021	*	Time
2	Matrix table with 3 statements and 5 scale points	Comfort using mobility currently (Fall 2021)	*	Time
3	Matrix table with 3 statements and 5 scale points	Comfort using mobility a year from now in Fall 2022	*	Time
4	Matrix table with 6 statements and 5 scale points	General attitudes and preferences	*	Mod.
5	Matrix table with 5 statements and 5 scale points	Public transit and COVID preferences	*	NC
6	Text entry	Public transit and COVID additional thoughts		NC
7	Matrix table with 6 statements and 5 scale points	Ride-hailing and COVID preferences	*	Mod.
8	Text entry	Ride-hailing and COVID additional thoughts		NC
9	Matrix table with 7 statements and 5 scale points	Attitudes and preferences on activities during COVID	*	Mod.
10	Multiple choice with 6 choices	Vaccination interest		New
11	Text entry	Additional thoughts on activities during COVID	*	New
12	Matrix table with 10 statements and 6 scale points	Frequency of modal usage during summer of 2021	*	Time
13	Matrix table with 4 statements a and 6 scale points	Frequency of technology usage during summer of 2021	*	Time
14	Matrix table with 10 statements and 6 scale points	Frequency of modal usage *currently*	*	Time

15	Matrix table with 4 statements and 6 scale points	Frequency of technology usage instead of a trip *currently*	*	Time
16	Multiple choice with 2 choices	Shared ride-hailing service suspension impact (Y/N)	*	NC
17	Text entry	Additional thoughts on transportation and COVID		NC
18	Text entry	Birth year	*	NC
19	Multiple choice with 6 choices	Educational background	*	NC
20	Multiple choice with 3 choices	Gender identity (M/F/S)	*	NC
21	Multiple choice with 2 options	Hispanic (Y/N)	*	NC
22	Multiple choice with 5 options	Race (multiple answer choices)	*	NC
23	Text entry	Zip code	*	NC
24	Multiple choice with 7 options	Current employment situation (Multiple answer choices)	*	NC
25	Multiple choice with 2 choices	Employment situation changed since May 2021 (Y/N)	*	Time
25b	Multiple choice with 7 options	Prior employment situation (Multiple answer choices)		Time
26	Multiple choice with 6 choices	2019 Household income	*	NC
27	Form field with 2 fields	Email and phone number		NC
28	Text entry	Additional thoughts on topic		NC

* = required response

NC = no change, Time = updated time frame, Mod. = Modified (added or removed) statements

3.3. Results and Discussion

3.3.1. Participation and Data Quality

Concerns regarding potential professional survey takers and survey fraud from bots and speeding respondents in many online surveys have long plagued online survey recruitment methods. Poorly chosen recruitment and distribution channels can lead to biased data and low response rates. This section compares participation and data quality collected from the study's five sampling methods to identify potential data concerns.

Five types of data quality checks were performed; 1) participants who did not fully complete the survey, 2) participants who took less than 2 minutes to complete the questionnaire (short completion time suggested random clicking), 3) participants who lived outside of the study area of the Atlanta metro area, 4) participants who did not answer an attention check question correctly, and 5) participants who answered open-ended responses incoherently. The attention check question was a part of the frequency of the model usage question set. If respondents indicated the use of shared ride-hailing during the pandemic, the survey was removed from the dataset. Shared ride-hailing service has been suspended since March 2020 so if a participant indicates this, they were inattentive or inaccurate. Figure 3-2 provides a visual explanation of the recruitment and cleaning process for this survey effort and Table 3-3 provides a summary of response analysis. The Wave 1 sample recruited a total of 1456 attempted responses, 930 of which were completed responses. The completion rate of the full

Wave 1 survey was 63.9%; calculated by dividing the number of users who completed the survey by the total number who attempted to complete the survey. The majority of participants who did not complete the survey stopped at the modal usage frequency matrix portion of the survey. The response rate of the survey was calculated by dividing the number of people who completed the survey by the number of people who made up the total sample group. For the community outreach, Qualtrics, and Mechanical Turk recruitment methods the total sample groups were not accessible (i.e., the number of people who had actually seen or received the recruitment materials could not be determined) so sample response rate were not evaluated. Only 787 of the completed responses passed all five “quality” checks. The “quality” completion rate was calculated by dividing the number of respondents that passed all quality checks by the number of respondents that started to complete the survey. For the combined sample, the “quality” completion rate was 54.0%. The “quality” screened-in rate was represented by the number of “quality” responses over the number of completed responses and was 82.6% for the combined sample.

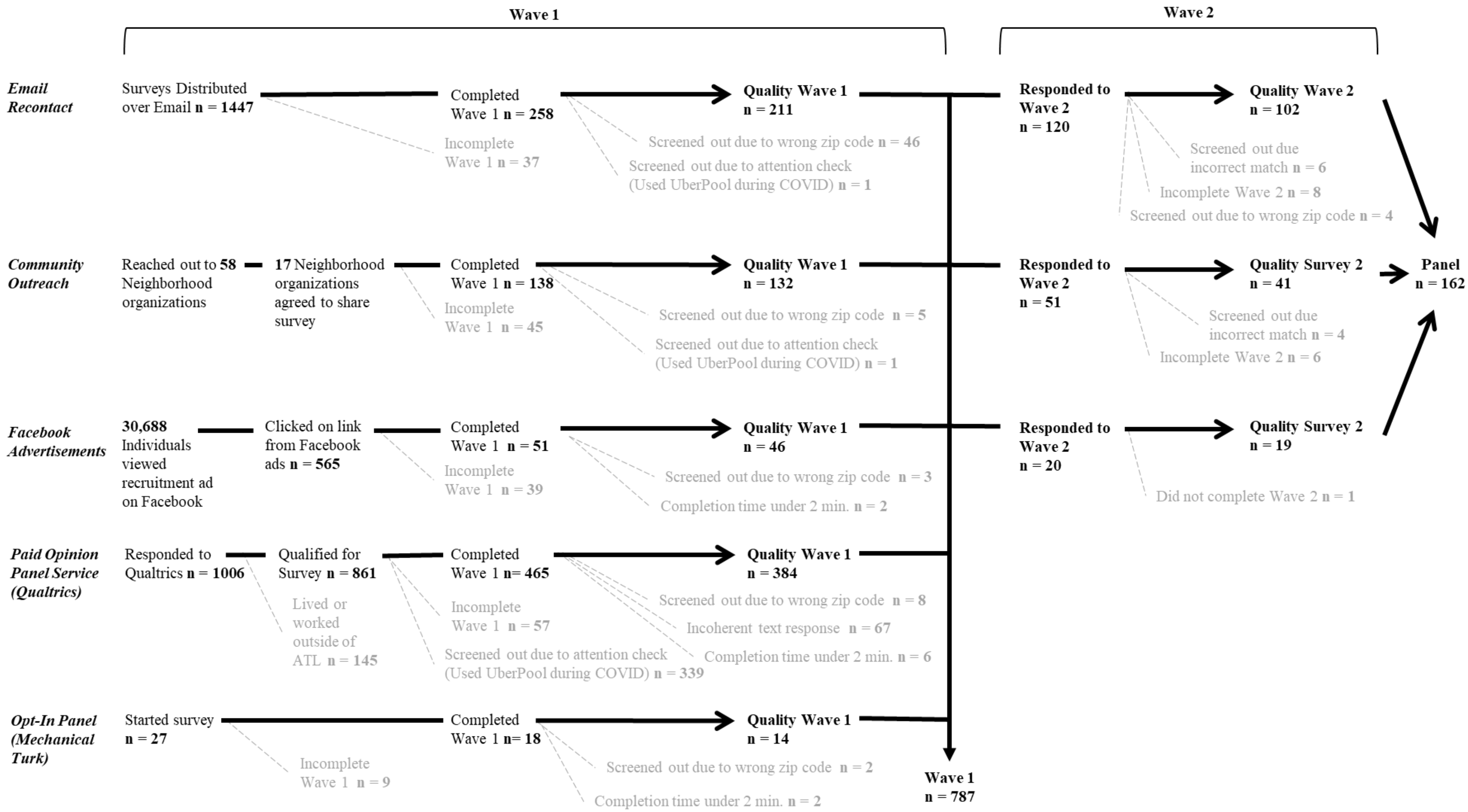


Figure 3-2: Respondents in Two-Wave Survey Flow Chart

TABLE 3-4: RESPONSE RATE, COMPLETION RATE, AND "QUALITY" COMPLETION RATE BY RECRUITMENT METHOD

Recruitment Method	**Email Recontact**	**Community Outreach**	**Facebook Ads**	**Paid Opinion Panel**	**MTurk**	**Combined**
Sample Size	1447	-	565	-	-	-
Started Survey	295	183	90	861	27	1456
Completed Survey	258	138	51	465 *	18	930
Passed Quality Check	211	132	46	384	14	787
Response Rate	17.8%	-	9.0%	-	-	-
Completion Rate	87.5%	75.4%	56.7%	54.0% *	66.7%	63.9%
“Quality” Completion Rate	71.5%	72.1%	51.1%	44.6%*	51.9%	54.0%
“Quality” Screened-In Rate	81.8%	95.7%	90.2%	82.6%*	77.8%	84.6%

* Participants who did not answer the attention check correctly were not allowed to complete the survey

The email recontact distribution method sample involved sending out 1447 emails with an invitation and link to complete the survey. Of the 1447 emails distributed from the email recontact sample, 295 respondents started to complete the survey but only 258 respondents ultimately completed the survey (response rate of 17.8% and completion rate of 87.5%). Recruitment through community outreach resulted in 211 quality surveys (quality completion rate of 71.5% and screened quality rate 81.8%) after removing 37 incomplete surveys, screening out 46 responses with a zip code outside of metro Atlanta, and one respondent who indicated the use of shared ride-hailing during the pandemic. The low response rate of 17.8% may have resulted from the large time gap between the initial and subsequent survey requests and a lack of monetary incentive. However, 17.8% was still a far higher response rate than could be expected from an entirely new recruitment using address-based surveys.

The community outreach method distributed the survey by social media/newsletters from 17 community organizations around Atlanta. This effort resulted in 138 respondents who completed the survey and 45 respondents who began the survey but did not complete it (completion rate of 75.4%). Of the complete surveys, only six were screened out due to zip code (n=5) or attention check error (n=1) resulting in a high “quality” screened-in rate of 95.7%.

To recruit participants through social media, the Facebook advertisement was displayed on a screen 91,323 times (impressions) and 30,688 people saw the ad at least once (reach) during the survey period. Although the link on the ad was clicked 639 times resulting in 565 unique clicks, only 90 people began the survey and 51 completed it. Although true response rate cannot be calculated, assuming the 565 who clicked on the ad as the sample, the social media ad had a response rate of 9.8%. Half of the incomplete surveys resulted from respondents opening the survey and clicking past the first page but not actually participating. Of the completed surveys, three contained a zip code outside of Atlanta and two failed the attention check, resulting in a high “quality” screened-in rate of 90.2%. The 51 completed surveys collected through social media provided good data quality with thoughtful optional fill-in responses and lack of incoherent open-text responses.

The online paid opinion panel, Qualtrics Panel services, sent out the survey to their sources with the goal of 400 clean and complete surveys. Although we do not have access to the number of initial request emails or other recruitment methods used, the full dataset was accessible even though the Qualtrics Panel employee who managed the dataset provided a final clean dataset. As the survey was targeting individuals in the Atlanta metro area that were 18+ years of age, a screener question (the same question used in MTurk) was added. Of the 1006 participants that answered the screener question, only 861 participants qualified to continue. If they failed to qualify into the survey, the survey would automatically terminate. Those screened out of the process included 21 people from Augusta, 16 from Columbus, 9 from Macon, 7 from Savannah, and 94 from other cities. Surveyors who failed to pass the shared ride-hailing attention check were also terminated before completing the survey. Almost half (40%, n=339) of people who qualified for the survey were screened out due to incorrectly answering the attention check. A smaller portion (n=57) did not finish the survey to completion. This resulted in a completion rate of 54.0% and 465 completed surveys. These were further examined for data quality concerns which identified 14.4% (n=67) of the completed surveys providing incoherent or inappropriate responses in the optional fill-in-the-blank text entry (e.g. “Special Collections and University Archives invite you to help us capture and preserve our communities’ experiences of the COVID-19 pandemic”, “B going ffbllnv”, and “a hey hey ya all mama finna I was lik”), 1.7% (n=8) participants who inputted zip codes outside of Atlanta (despite qualifying into the survey by indicating they were from the metro Atlanta area), and 1.3% (n=6) participants who completed the survey in under 2 minutes, finally resulting in 384 quality surveys. Although the screened quality rate was high at 82.6%, this value did not capture the responses that did not pass the attention check as these respondents were not allowed to finish the survey. If the 339 responses that failed the attention check had completed the survey and were not forced to exit the survey early, the “quality” screened-in rate would have been 47.8%.

MTurk only had 27 workers start the HIT task and survey. This low number may be due to the implementation of a screening question; workers had to answer a single multiple-choice question to identify the metro area they live in; “Do you live or work in any of the following Georgia areas (including the surrounding suburbs / greater metro area)”. If they answered anything besides Atlanta (i.e. Augusta, Columbus, Macon, Savannah, or “I live in a different area”), they were not granted the qualification for the survey and could not submit the HIT for a reward. The screener question could only be attempted a single time. Ibarra et al. (2018) collected a similar low yield of responses with quality and verification screening implemented [33]. The few responses the 2018 study did receive were of a high-quality after screening out by respondents by reputation; unlike Eyal et al (2021) who found MTurk low data quality even with data quality filters. In our study, although 27 workers started the survey, only 18 respondents ultimately completed the survey (completion rate of 66.7%). Four surveys were removed due to data quality issues (e.g. two due to speediness and two due to zip code outside of Atlanta) which resulted in a very small sample (n=14).

Overall, the paid opinion panel (Qualtrics) recruited the largest volume of participants (n=861) but also experienced large data quality issues with only 44.6% of the collected surveys completed without error. These errors were primarily from respondents missing the attention check (n=339) and incoherent text responses (n=67). The two crowdsourcing platforms of Facebook Ads and Mechanical Turk experienced low rate of quality surveys (51.1% and 51.9%) and relatively low volumes of quality surveys (n=46 and n=14). The email recontact and community outreach methods resulted in large volumes of quality respondents (n=211 and n=132) with the highest quality completion rates (71.5% and 72.1%). Respondents were primarily screened out of these two methods due to zip code errors which may be explained by respondents not updating their address.

3.3.2. Cost and Efficiency

Online survey recruitment methods differ significantly in terms of cost and process because of their unique payment structures facilitated by recruitment platforms. Using MTurk, researchers can set their own price and budget and "pay per completed task", while Qualtrics Panel involves a contract and paying a minimum fee per completed survey. Facebook advertisements have a variety of payment options and scenarios to pay when ads are clicked or shown. As seen in Figure 3-3, the most expensive survey was incurred though Facebook advertising which cost $521 and resulted in only 48 surveys ($10.85 per quality survey). Due to the low number of responses and high costs, the research team ended the Facebook Advertising two weeks earlier than the remaining survey recruitment channels. Although our survey effort did not find Facebook advertisement as an effective recruitment methodology a large literature has successfully implemented social media surveys for less than $0.50 per full response. The low-quality response rate might be due to design flaws in the visual advertisement or a less optimal sampling frame for this method; previous studies targeted large areas and entire nations [27, 34], while others target small niche attributes [35-36].

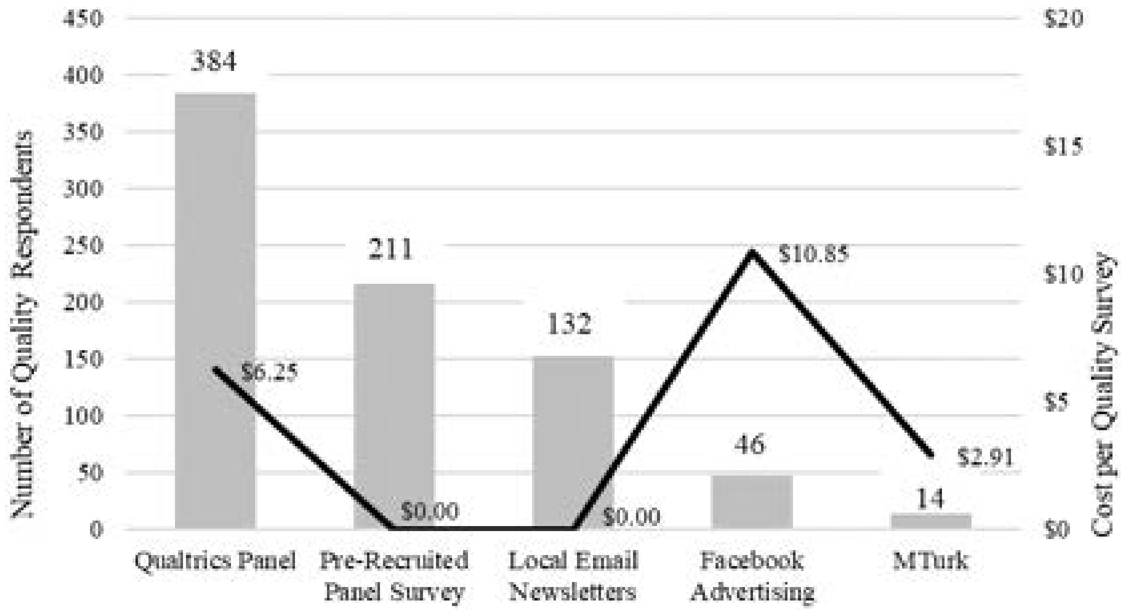


FIGURE 3-3: NUMBER OF QUALITY RESPONDENTS AND COST PER QUALITY RESPONDENT BY SAMPLING METHODOLOGY

In addition to monetary costs, each method required time and effort for implementation. The MTurk sample took the most prep time due to an outdated user interface, coding in the AWS to implement a screener question, setting and testing the HIT in the MTurk Sandbox, and advertising the HIT. A medium level of effort was put into the Facebook Advertising survey campaign and community outreach sample. Although the researcher has to design an advertisement and copy text, create a landing page for the survey, and monitor survey progress, Facebook's easy user-interface lessened the mental load. The effort spent establishing the list of potential local organizations with contact information and reaching out to each with a personal email proved to be fruitful with 153 respondents and a contact list that can be used for future surveys. Qualtrics Panel service required only minimal efforts of email correspondence to set up survey expectations and data cleaning.

The survey was first published on October 14, 2020 and concluded on November 18, 2020. Data was collected the quickest through the use of Qualtrics Panel. The community outreach method required the longest collection time as organizations would post or share the survey during planned meetings or monthly newsletters.

3.3.3. Ability to Collect Private Contact Information from Respondents

Unlike a single cross-sectional survey, which can only be used to draw conclusions about a snapshot of the population at a certain time, analysis of longitudinal survey data has the potential to illuminate how the population is changing. A longitudinal panel survey can be conducted by repeating a survey to the same group of participants. This requires the collection of some participant contact data like email address or phone number. Collecting this personal information from respondents removes the anonymity of an online survey but provides the potential opportunity to send a follow-up survey.

Each survey recruitment method establishes different standards and regulations on collecting personal information. MTurk prohibits the collection of any personally identifiable information (including email address and phone number) but does allow HIT requesters to reach out to specific respondents through the MTurk platform based on the previous tasks' collected Worker IDs. Google Surveys service does not allow the collection of any personally identifiable information and has no way of re-contacting participants. Qualtrics panel service can be contracted to pursue a follow-up survey at a future agreed upon date if initially positioned as a longitudinal study. Qualtrics collects respondent ID from completed surveys and sometimes has the ability to use the respondent ID to reach out to participants again. As the company uses third-party vendors and some vendors were unable to conduct follow-up studies, the intentions of a longitudinal study must be stated from the beginning of the initial survey effort and the follow-up study must be conducted through the Qualtrics panel service platform for a fee. If a surveyor would like to privately contact respondents without Qualtrics as a middleman, the initial survey can collect personally identifiable information (PII) for an additional fee. Cost estimates from this research study indicated that collecting email addresses with the survey would double the originally quoted price ($2400 to $4700). Although this study did intend to perform a second-wave data collection through Qualtrics Panel, a miscommunication resulted in the inability to recontact respondents.

The second wave survey, a year after the initial survey, resulted in 176 completed survey responses. The majority of these respondents were initially recruited through the email recontact method, as seen in Table 3-4, which yielded the highest recontact response rate (percent of prior respondents with available private contact data that responded to Wave 2). Community outreach and Facebook ads recruitment methods recorded similar percentages of effective contact information.

TABLE 3-5: POTENTIAL FOR PRIVATE CONTACT OF RESPONDENTS

Recruitment Method	Wave 1 Responses	Private Contact Data Available		Wave 2 Responses	Recontact Response Rate
Qualtrics	384	0	(0.0%)	-	-
Email Recontact	216	173	(80.1%)	120	69.4%
Community Outreach	153	74	(64.5%)	51	68.9%
Facebook Advertisements	48	31	(60.8%)	20	61.3%
MTurk	14	0	(0.0%)	-	-
Combined Sample	829	278	(33.5%)	171	63.3%

3.3.4. Demographics of Recruited Participants

Although this study did not attempt to obtain a representative sample, we compared demographic information, including gender, age, income, and education across different methods as displayed in Table 3-5. The breakdown of demographic information for each mode was further compared against the actual population breakdown with chi-squared tests for significance performed between methods and the American Community Survey (ACS) population. The community outreach and Facebook advertisements over-recruited females when compared with the Atlanta population and the other sampling methods. As both methods relied on social media, this finding of a female-skew through social media recruitment was consistent with existing literature [30,37].

Although no method was able to recruit a truly representative sample of race / ethnicity, Qualtrics Panel was the closest to a representative sample in terms of ethnicity. All methods over-sampled white people while under-sampling African Americans. Only the community outreach and Qualtrics Panel distribution methods significantly over-recruited participants with higher education. None of the methods met the Atlanta population demographic spread for age. MTurk and Qualtrics Panel, the two "pull in" methods where participants were seeking out surveys, over-sample a slightly younger crowd. The email recontact, Facebook ads, and community outreach failed to capture this younger audience. Finally, the distribution of income among respondents was significantly different for all of the distribution methods except for the online opinion panel. The email recontact and community outreach samples were heavily skewed towards higher incomes. No single platform recruited a representative sample regarding socio-demographics which was mainly due to the non-probability nature of the convenience online methods.

TABLE 3-6: PERCENTAGE POINT DIFFERENCES FROM POPULATION AND RESPONDENT SOCIO-DEMOGRAPHIC ATTRIBUTES BY RECRUITMENT METHOD

	% of Atlanta Pop. [a]	Email Recontact (n=211)	Facebook Ads (n=46)	Community Outreach (n=132)	MTurk (n=14)	Qualtrics Panel (n=384)	Combined Sample (n=787)
		Percentage Point Differences between Population and Respondents					
Gender							
Female	51.7	+ 4.3	+ 31.6	+ 14.3	+ 8.3	- 4.8	+ 3.6
Race / Ethnicity							
White / Caucasian	45.9	+ 28.6	+ 37.4	+ 41.7	+ 34.1	+ 16.3	+ 25.9
African American	34.2	- 14.8	- 17.5	- 29.0	- 20.9	- 3.7	- 12.5
Hispanic	11.0	- 6.4	- 10.5	- 7.8	- 11.0	+ 2.7	- 6.6
Asian	6.1	- 2.4	- 1.9	- 0.9	+ 7.2	- 1.7	- 1.6
Education							
Bachelor's degree or higher	39.9	+ 32.1	+ 45.1	+ 54.1	+ 45.1	+ 24.1	+ 34.1

TABLE 3-5: CONTINUED	% of Atlanta Pop. [a]	Email Recontact (n=211)	Facebook Ads (n=46)	Community Outreach (n=132)	MTurk (n=14)	Qualtrics Panel (n=384)	Combined Sample (n=787)
		Percentage Point Differences between Population and Respondents					
Age							
18-34	31.8	- 21.6	- 19.3	- 16.1	+ 14.8	+ 4.9	- 7.3
35-49	27.8	+ 19.0	- 0.7	+ 7.5	+ 5.5	+ 18.0	+ 15.0
50-64	24.8	+ 4.8	+ 10.6	+ 5.9	- 11.5	- 11.0	- 2.4
65+	16.7	- 3.3	+ 8.3	+ 1.6	- 10.0	- 13.1	- 6.4
Income							
Less than $25,000	14.7	- 11.5	- 2.2	- 13.4	- 14.7	- 0.1	- 6.0
$25,000 - $49,999	19.2	- 5.3	- 4.6	- 10.6	+ 7.5	- 3.3	- 5.1
$50,000 - $74,999	18.2	- 1.1	- 1.5	- 11.6	+ 8.5	- 3.9	- 4.2
$75,000 - $99,999	13.2	- 2.1	- 7.0	- 3.3	+ 20.1	+ 2.2	- 0.2
$100,000 - $149,999	16.8	+ 5.4	+ 6.1	+ 12.3	- 10.1	+ 3.3	+ 5.4
More than $150,000	17.8	+ 14.6	+ 9.3	+ 26.6	- 11.1	+ 2.0	+ 10.1

[a] From 2019 ACS estimates

3.3.5. Mobility Patterns of Recruited Participants

As the most common mode of transportation in the US is a personal vehicle, shared mobility users, such as frequent users of shared ride-hailing, may be considered harder-to-reach populations. To understand the best modes to recruit these specific populations, the frequencies of ride-hailing (Uber), shared ride-hailing (UberPool), and public transit are shown in Table 3-6. "Non-Users" indicated that before the COVID-19 pandemic they had not used the mode in the last month and "Active Users" indicated that they used the mode at least once a week. Respondents who used an alternative mode of transportation (i.e. ride-hailing, shared ride-hailing, scooters, biking, shared biking, and transit) at least once a week were labeled as "Multimodal Lifestyle". Differences of mobility patterns by sampling methods are indicated by significant chi-square tests.

The online opinion panel recruited the largest number and percentage of active ride-hailing users, active shared ride-hailing users, and active bus riders; the Qualtrics sample contained at least twice the percentage of active ride-hailing and bus users and four-times the percentage of active ride-hailing users as the other samples. The MTurk method resulted in the most non-users for ride-hailing while the Facebook ad distribution method resulted in the most non-users for shared ride-hailing. All sampling methods recruited significantly more active and occasional users for rail than for bus despite similar levels of ridership for bus and rail in the Atlanta-metro area [38].

TABLE 3-7: RECRUITMENT OF SHARED MOBILITY USERS BY SAMPLING METHOD (%)

	Email Recontact (%) (n=211)	Facebook Ads (%) (n=46)	Community Outreach (%) (n=132)	MTurk (%) (n=14)	Qualtrics Panel (%) (n=384)	Combined Sample (%) (n=787)
Ride-Hailing						
Non-User	7.6 **	17.4	4.6 **	21.4	19.3 ***	13.6
Occasional User	78.7 ***	73.9	78.0 **	64.3	54.2 ***	66.1
Active User	13.7 **	8.7 *	17.4	14.3	26.6 ***	20.3
Shared Ride-Hailing						
Non-User	49.8	76.1 ***	59.1 *	64.3	42.5 ***	49.6
Occasional User	47.9	23.9 **	37.9 *	35.7	44.0	42.7
Active User	2.4 **	0.0 *	3.0	0.0	13.5 ***	7.8
Bus						
Non-User	61.1 *	67.4	71.2 **	64.3	42.7 ***	54.3
Occasional User	32.2 **	28.3	20.5 **	28.6	38.0 **	32.8
Active User	6.6****	4.4	8.3	7.1	19.3 ***	13.0
Rail						
Non-User	14.2 ***	28.3	15.9 ***	42.9	34.4 ***	25.7
Occasional User	67.8 ***	60.9	64.4	50.0	49.0 ***	57.3
Active User	18.0	10.9	19.7	7.1	16.7	17.0
Multimodal Lifestyle	35.7	10.9 ***	35.7	14.3	38.8	35.7

Pearson's Chi-Squared Significance Test on group differences
*** p-value < 0.001, ** p-value <0.01, * p-value < 0.05

3.3.6. Attitudes and Behavior of Recruited Participants

In addition to sampling different demographics and modal preferences, survey methodologies captured different participant attitudes as seen in Table 3-7. There was a statistically significant difference between most of the attitudes in the Qualtrics Panel and the remaining combined sample as determined by one-way ANOVA. Respondents in the Qualtrics Panel sample were on average more uncomfortable around strangers, more likely to carry hand sanitizer, and more germ-conscious than the rest of the panel. Many of the attitudes of the email recontacts also differed from those of the rest of the sample. Interestingly, the community outreach sample trended to be the most social sample (e.g. on average agreeing that they miss small interactions with strangers and disagreeing they were uncomfortable around strangers) while the MTurk sample was the least social sample.

TABLE 3-8: AVERAGE ATTITUDES BY SAMPLING METHOD

Attitude Statement	Average (Standard Deviation) Attitude by Sampling Method					
	Email Recontact	Facebook Ads	Community Outreach	MTurk	Qualtrics Panel	Combined Sample
I miss small interactions with strangers.	3.63 (1.02)	3.76 (1.04)	3.80 (1.03) *	3.00 (1.41) *	3.50 (1.13) *	3.59 (1.09)
I consider myself to be a sociable person.	4.08 (0.80)	4.02 (0.91)	4.20 (0.74)	3.36 (0.93) *	4.13 (0.90)	4.11 (0.86)
I'm uncomfortable being around people I don't know	2.77 (1.08) ***	2.74 (1.06)	1.77 (1.05) *	3.21 (1.12)	3.30 (1.12) ***	3.04 (1.13)
I always carry hand sanitizer.	3.02 (1.33) ***	3.72 (1.31)	3.01 (1.45) ***	3.50 (0.94)	3.84 (1.17) ***	3.47 (1.32)
My friends and family would describe me as "germ conscious".	3.07 (1.07) ***	3.17 (1.04)	3.26 (1.00)	3.00 (1.11)	3.52 (1.09) ***	3.33 (1.08)

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree
One-way ANOVA F-Statistic Significance *** p< 0.001, **p <0.01, * p< 0.05)

These attitude, modal, and demographic differences between samples may be a result of self-selection bias, which occurs when survey respondents are allowed to decide entirely for themselves whether or not they want to participate in a survey (which is, of course, always the case in a free society). To account for the bias resulting from over/under sampling particular socio-demographic characteristics, weighting cases to reflect the population distributions of characteristics such as gender, income, and age is a common approach. Over/under sampling particular groups may be due to the personality differences associated with being active online [8] and differences in the financial or social motivation to complete the survey [17]. However, data cannot be weighted with respect to attitudinal and personality variables because the weighting process requires the known population distribution of the characteristics in question. In this study, data was not weighted as the available Atlanta population demographic data might not be necessarily appropriate and correspond with the online targeted population. Even if the data were weighted, online survey results should be interpreted with care, as Correa et al. (2010) and Blasius and Brant (2010) found that personality traits influence online survey response even when controlling for socio-demographic traits [39-40]. Weighting data to best match the demographics of the population is especially important when establishing descriptive statistics but for understanding trends, modeling techniques can attempt to account for these characteristics.

To examine the potential impact of survey recruitment methods, this study developed four ordered logit models with added survey sampling method variables. The estimated models predicted the reported level of comfort using private ride-hailing before the pandemic. The dependent variable was measured by the Likert-style agreement (1 =Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, and 5= Strongly Agree) with the statement "Before COVID-19, I would have felt comfortable using...". Due to the ordinal nature of the data, a series of ordered logit models were developed as seen in Table 3-8. Independent variables in the models included attitudinal factor scores calculated from the factor analysis, socio-demographic binomial and numeric variables, and private ride-hailing prior modal usage binomial variables. Further explanation of this data, variables, and model development can be found in Chapter 4.3.3. of this report. Model fit was evaluated and reported by AIC, McFadden Pseudo R^2, McFadden Adjusted Pseudo R^2, and log-likelihood using Stata [41]. The McFadden's pseudo-R^2 formulation was one minus the model log-likelihood divided by the intercept-only log-likelihood. The adjusted McFadden Pseudo R^2 penalizes the McFadden pseudo R^2 as more variables are added to the model.

An initial model without the survey mode variables was first run to establish the impact of significant attitudinal and demographic variables. Two attitudinal factors, two demographic factors, and two prior usage factors explained the reported comfort using private ride-hailing before the pandemic. Each survey recruitment mode variable was added to the model sequentially. Model M1 displays the first addition of the paid panel service (Qualtrics Panel) variable. Adding this sampling method variable significantly improved the model fit statistically, as indicated by the likelihood ratio test comparing the improved model with the initial model (e.g. M0 compared to M1 in Table 3-8). The model with the survey mode variable had a lower AIC than the simple initial model, which also indicated that it may be a better fit. When comparing the initial model (M0) and M1, signs and magnitudes of the explanatory coefficients remain similar for all but the male variable in M1 which loses its significance.

In Model M2, the MTurk survey method variable was added to M1. This model was not a better fit than M1, as indicated by the likelihood ratio test between models. M2 is presented in Table 3-8 as it was the other sampling method variable to be slightly significant when included in the model. Examining the coefficients in M1, the comfort level for private ride-hailing will tend to decrease more (or increase less) if participants were sampled from the Qualtrics Panel than if they were sampled through other methods. In M2, the comfort level for private ride-hailing will also tend to decrease more (or increase less) if participants were sampled from MTurk than through other methods. The inclusion of the two sampling method variables in the M2 model indicated that the sampling method variables may represent one or more unobserved variables that impact comfort using private ride-hailing.

The remaining sampling method variables were added to the model one-by-one but were not displayed as they did not improve the model fit and were not statistically significant. The final model presented, M3, did significantly improve the model fit when compared to M2 but not all survey recruitment method variables included in the model were estimated to be significant. M3 shows that the inclusion of the other two sampling methods, community outreach and Facebook ad, did not substantially impact the magnitude of the other explanatory coefficients. These models indicated that even when controlling for socio-demographic variables, survey recruitment modes had the potential to impact attitudinal analysis. One explanation for this may have been the difference of motivation/purpose for survey participation in each sampling method. Both “pull in” sampling strategies (MTurk and Qualtrics Panel), which occurred when online users were actively looking to join a survey for paid work, were included in the model and helped explain the predicted level of comfort towards private ride-hailing. This finding, like other studies, indicated that these online panel members were not representative of the general population with respect to some attitudes [17,40]. Future work could expand this test on more attitudes and use weighted data to be more conclusive.

TABLE 3-9: ORDERED LOGIT REGRESSION MODELS OF COMFORT USING PRIVATE RIDE-HAILING BEFORE THE PANDEMIC, WITH AND WITHOUT SURVEY METHOD VARIABLES

Variable	M0 - No Survey Method Variables			M1- 1 Survey Method Variable			M2- 2 Survey Method Variables			M3- Full Model		
	Coefficient	p-value	Sig.	Coefficient	p-value	Sig.	Coefficient	p-value	Sig.	Coefficient	p-value	Sig.
Attitude Factors												
Follow Safety Measures	0.315	<0.000	***	0.256	0.001	**	0.236	0.002	**	0.242	0.002	**
Extrovert	0.250	0.001	**	0.236	0.003	**	0.229	0.001	**	0.229	0.004	**
Socio-Demographics												
Male Indicator	-0.314	0.042	*	-0.232	0.141		-0.237	0.134		-0.251	0.116	
Lower Income Indicator	-0.529	0.003	**	-0.444	0.013	*	-0.443	0.013	*	-0.433	0.016	*
Prior Usage Indicators												
Occasional User	1.864	<0.000	***	1.767	<0.000	***	1.759	<0.000	***	1.746	<0.000	***
Active User	2.010	<0.000	***	2.051	<0.000	***	2.047	<0.000	***	2.032	<0.000	***
Survey Recruitment Mode												
Paid Panel Service				-0.646	<0.000	***	-0.712	<0.000	***	-0.750	<0.000	***
MTurk							-1.080	0.03	*	-1.118	0.028	*
Community Outreach										0.008	0.977	
Facebook Ad										-0.318	0.381	
Thresholds												
μ_1	-2.948			-3.299			-3.388			-3.440		
μ_2	-2.108			-2.458			-2.539			-2.592		
μ_3	-1.057			-1.408			-1.479			-1.533		
μ_4	0.866			0.534			0.469			0.415		
AIC	1433.12			1419.12			1416.77			1419.95		
McFadden Pseudo R^2	0.094			0.104			0.107			0.107		
McFadden Adjusted Pseudo R^2	0.081			0.090			0.091			0.089		
LL(full)	-706.56			-689.56			-696.38			-659.97		
Prior Model Likelihood-Ratio Test	-			LR=-34, df=1, p-value ≤ 0.001			LR=13.646, df=1, p-value = 0.462			LR=-58.64, df=2, p-value≤ 0.001		
# of Responses = 787, LL(intercept-only) = -779.446												

3.4. Conclusion

When conducting online survey research, the sampling methodology is extremely important to the quality and representativeness of the sample. Trade-offs between effort, time, and money limit the amount and quality of survey responses in online survey recruitment methods. In this survey effort, the goal was to examine the process and outcomes of different online recruitment methods. Five online sampling techniques were implemented and summarized in Table 3-9: 1) email recontact of respondents from past transportation surveys, 2) social media ads, 3) community outreach, 4) Mechanical Turk, 5) and paid panel service. The Google Survey service, a survey pop-up wall on websites, was not implemented due to privacy concerns. Mturk and the paid panel service both actively recruited (pulled in) participants and offered a monetary incentive. The other three methods involved pushing out ads and letters to recruit participants who were not actively seeking involvement in a survey. The paid panel service recruited the largest number of responses (384 respondents), which accounted for 48.8% of the combined sample (n=787). The second most productive effort (26.8%) resulted from reaching out to participants from previous surveys (211 respondents), as summarized in Table 3-9.

The paid panel service and email recontact methods required the lowest level of effort from the researcher and therefore, could be used for quick implementation of a survey. However, quick implementation comes with a financial and data quality cost. The Qualtrics panel cost more than the email recontact sample ($6 vs $0 per quality survey response) but it was not the most expensive method; Facebook ads cost more than $10 per quality respondent. Previous studies have been more successful in collecting survey participants from Facebook Ads and MTurk but due to different implementation options (of which there are a plethora) our study did not observe similar results. Although the sample recruited through Facebook ads suffered from low completion rates, the respondents who did complete the survey were not observed to have many errors and were willing to be part of future survey efforts. Issues were observed in the paid online panel service sample; incoherent/inappropriate answers occurred in the optional text responses and almost half of the participants failed the attention check by reporting that they had used shared ride-hailing during the pandemic.

Differences in sample motivations for participation, as well as coverage differences, resulted in demographic and attitudinal differences between methods. No platform recruited representatively across demographic traits and modal frequencies. In particular, community outreach and Facebook advertisement over-recruited females while community outreach and Qualtrics Panel over-recruited higher educated participants. Shared ride-hailing users were best captured by the online opinion panel. This finding was promising due to the hard-to-reach nature of these users and the fast, cheap, and high response rate from this platform. The community outreach sample was on average more extroverted while the MTurk sample was less extroverted. Exploratory analysis of respondent attitudes by sampling methods suggested that for methods where an online user was actively seeking work, i.e. Qualtrics and Mturk, the respondent's attitude differed even when controlling for demographics. Although online samples lack demographic and attitudinal representativeness, they can still provide valid inferences and can be optimized to target specific populations. A mixed-recruitment sample that combines these methods can be utilized to provide a more full and complete dataset as long as the impact of the limitations in each recruitment method are understood.

TABLE 3-10: SUMMARY OF RECRUITMENT METHOD OUTCOMES

	Opt-in Participation from Past Survey Efforts (Email Recontact)	Facebook Ads	Community Outreach (Local Newsletters and Media)	Mechanical Turk	Paid Panel Service (Qualtrics Panel)
Survey Mechanism	Push out	Push out	Push out	Pull in	Pull in
Effort of Data Collection	Low Effort	Medium Effort	High Effort	Medium/High Effort	Low Effort
Cost Per Respondent	NA	$10.85	NA	$2.91	$6.25
Survey Completion Rate	87.5%	56.7%	75.4%	66.7%	54.0%*
Data Quality Concerns	Incorrect zip codes	Minimal	Minimal	Incorrect zip codes Speeding	Incoherent/ inappropriate text responses Attention check failures
"Quality" Completion Rate (# of responses that passed all quality checks / # of responses that started to complete survey)	71.5%	51.1%	72.1%	51.9%	44.4%
# of "Quality" Responses	211	46	132	14	384
Screened "Quality" Rate (# of "Quality" Responses / # of Completed Surveys)	81.8%	90.2%	95.7%	77.8%	82.6%*
Ability to Collect Private Contact Info	High	High	High	None	For an additional cost
Demographic Representation	Over-sampled white and highly educated Older sample (35+)	Heavily over-sampled white and highly educated Over-sampled females Older sample (50+)	Heavily over-sampled white and highly educated Older sample (35+) Over-samples higher income ($100K+)	Heavily over-sampled white and highly educated Younger samples (<50)	Over-samples white and educated Younger samples (<50)

TABLE 3-11: CONTINUED					
	Opt-in Participation from Past Survey Efforts (Email Recontact)	**Facebook Ads**	**Community Outreach (Local Newsletters and Media)**	**Mechanical Turk**	**Paid Panel Service (Qualtrics Panel)**
Sample Mobility Usage	High % of rail active users	Highest % of shared ride-hailing non-users	Highest % of rail active users	Highest % of non-users rail	Highest % of active bus, shared ride-hailing, and solo ride-hailing users
Attitudes			Most social	Less social Significant in solo ride-hailing comfort model	More germ-phobic Significant in solo ride-hailing comfort model
* Participants who did not answer the attention check correctly were not allowed to complete the survey					

4.0. Impact and Analysis of Rider Comfort in Shared Modes During the COVID-19 Pandemic

4.1. Introduction

The novel coronavirus (COVID-19) pandemic dramatically impacted the way people around the world work, socialize, and travel. The virus responsible for COVID-19, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was most commonly spread between people who were in close contact with one another as it moves through respiratory droplets [1]. To reduce potential exposure, individuals around the world chose to work from home, only leave for essential trips, and travel with as little contact with strangers as possible. Crises and other network disruptions, like the pandemic and associated social distancing trends, resulted in long-lasting changes in travel behavior and travel demand including modal switches and changes to travel frequency [2]. Attitudes and activity patterns changed, as many transportation options were considered unsafe or unavailable. In particular, shared mobility saw a significant decrease in usage as the COVID-19 risk reduced people's willingness to share a ride [2-5]. Shared mobility, which includes bike-sharing, carsharing, public transit, paratransit, and ride-sourcing services such as Uber and Lyft, can be defined as transportation involving multiple users sharing services and resources concurrently or one after another [6]. Prior to the pandemic, shared mobility was associated with positive benefits such as reduced traffic congestion, lower greenhouse gas emissions, and smaller parking demand. The post-COVID period, often referred to as the "new normal", may reflect several scenarios including shared mobility options returning to business as usual, becoming less attractive compared to private travel options, or disappearing completely [7-8]. The longer-term impacts of the pandemic on shared mobility are still unknown.

To gain insight into the impacts of COVID-19 on shared mobility, we developed an online reported-revealed preference survey to measure the comfort and usage of users with respect to three types of shared mobility -- private ride-hailing, shared ride-hailing, and public transit -- during the periods before, during, and after the COVID-19 pandemic. As Georgia was one of the first U.S. states to reopen, the Atlanta metro area population can provide useful insight into the future. The collected data explains changes in shared mobility usage due to varying levels of willingness-to-share before and during the pandemic. Little was known about how changes in shared mobility comfort may persist in a post-pandemic future. This research bridges gaps in knowledge related to COVID-19 and shared mobility so transportation policy and plans can best reflect changes in the "new normal".

4.1.1. Response to the COVID-19 Pandemic in Georgia

After COVID-19 was declared a national emergency in the U.S. on March 13, 2020, the state of Georgia declared a state of public health emergency on March 14, requiring all public schools, colleges, and universities to close. To curb the spread of the virus, Georgia implemented a shelter-in-place order, a ban on gatherings over 10 people, and the closure of bars and nightclubs on March 23, 2020. The Metropolitan Atlanta Rapid Transit Authority (MARTA), the primary public transportation operator in the Atlanta metro area, reduced rail and bus operations, removed bus fares, and implemented rear-door boarding on March 30 in response to the pandemic. Georgia was one of the first states to reopen in the U.S. On May 1, Georgia's shelter-in-place order for the public expired allowing businesses and restaurants to re-open with capacity limits. Bars and nightclubs in Georgia would begin to re-open in June. Amid a local surge in the virus in mid-July, Atlanta's mayor signed an order requiring masks to be worn in businesses. Figure 4-1 displays the new positive cases, hospitalizations, and deaths associated with COVID-19 over time in Georgia. After peaking in mid-August, COVID cases were on the decline in Georgia until mid-October [9]. As of December 2020, the public health state of emergency, social distancing guidelines, and local option face-covering requirements were still in effect in Georgia [10]. MARTA resumed normal front-door boarding and fare collection on September 2020 and increased rail and bus operations in April 2021 [11-12].

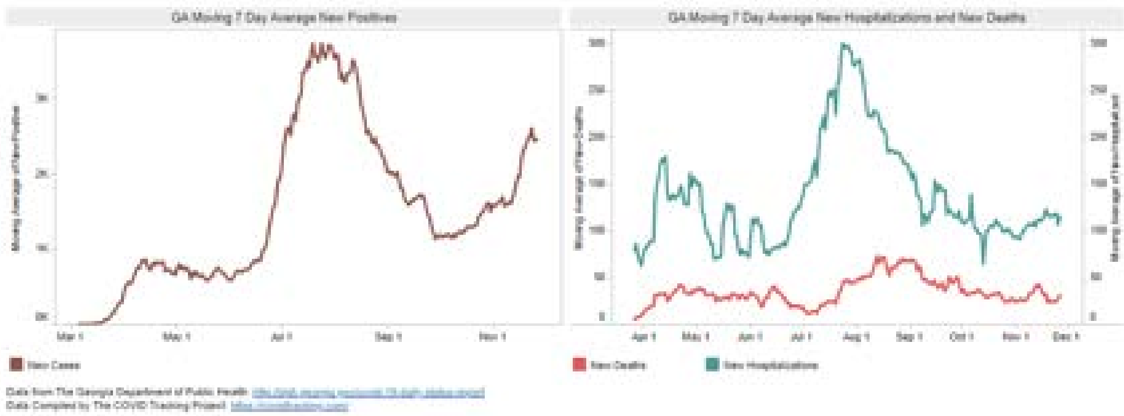


Figure 4-1: Key indicators of COVID-19 levels in GA (Georgia COVID-19, 2020)

In addition to MARTA, other shared mobility services reduced or suspended services during phases of the pandemic in Atlanta. Micromobility e-scooter services including Bird and Uber's JUMP were suspended from April to July. Nationwide, shared ride-hailing services including UberPool and Lyft Shared were suspended indefinitely on March 17. For the first few months of the pandemic, TNCs encouraged people to only use ride-hailing services for essential trips. In May 2020, Uber and Lyft outlined measures and precautions for ride-hailing services including passenger limits, face mask requirements for drivers and passengers, a requirement for passengers to ride in the back seat, encouragement of air circulation with rolled down windows, and a vehicle cleaning guide. During the pandemic, ride-hailing services continued efforts to reduce risk by introducing contact tracing and by distributing additional masks and sanitizing products.

4.1.2. Impact of COVID-19 pandemic on Shared Mobility

A growing number of studies have examined the impact of COVID-19 on transportation behaviors during the pandemic. During the early months of the pandemic, March and April, the number of trips for all modes significantly dropped [4,13-14]. In addition to examining actual usage, customer attitudes indicated a significant drop in usage of public transit and ridesharing apps and services [15]. These early trends and predictions motivated further research into the potential long-term impacts on behaviors and preferences. A survey in April 2020 found that 39% of those who previously used ride-sharing, and 45% of those who previously used public transportation, expected they would decrease or stop their use when economic activity resumes [16]. As the pandemic continued into the summer, two research studies attempted to examine the current and future impact of COVID-19 on transportation behavior by collecting survey data across the U.S from April to June [5,17]. Major current and future trends from these studies included an increase in work from home and a potential shift from shared mobility options such as pooled ridesharing and transit services. The decreased in usage of transit, pooled ride-hailing, and ride-hailing during the pandemic was likely due to the high perceived risk from these travel modes [5]. While the majority of survey respondents expected their use of various modes in the “new normal” to return to levels before the pandemic, a significant minority expected a change likely due to new work-from-home options [17]. A large survey collection effort related to transportation behavior and COVID-19 occurred in July and August 2020 [18]. Similar to previous surveys, a large majority of respondents (more than 60%) expressed some skepticism in their use of shared transportation modes such as public transit, shared ride-hailing, and private ride-hailing during the pandemic. This trend of skepticism in shared mobility was predicted to continue even once the COVID-19 pandemic was no longer a threat.

As conditions surrounding the pandemic continued to change through Fall 2020 and Winter 2021, this study aimed to enhance the literature on mobility preference during the pandemic and identify potential trends in a post-pandemic world. This paper presents reported preference survey data from a snapshot of time during the pandemic. The goal of this research was to examine the comfort and usage of shared mobility before, during, and after the pandemic to provide a better understanding of the potential future impacts of COVID-19.

4.2. Data and Methodology

To assess the reported and revealed preferences of transportation users in the Atlanta area, a brief online survey was designed and developed to be completed in 10 minutes or less with five short sections. The length of the survey was mindful of participant time to more likely result in a high response rate. The first set of questions collected participants' level of comfort on different shared modes during three time periods: the period before COVID-19, the current time when they completed the survey, and a future period when a COVID-19 vaccine became available. A definition of each shared mode was included in this section to familiarize participants with the terms used in the survey. After indicating their level of comfort on a Likert-scale, the survey included a series of Likert-scale general attitude statements and opinion statements related to existing COVID-19 procedures in transit and ride-hailing. The third and fourth sections were designed to collect frequencies of trip usage for different modes in a typical time before the COVID-19 pandemic and in the past month during the COVID-19 pandemic. The fourth section included an attention check, based on the knowledge that shared ride-hailing services were suspended during the pandemic, which enabled us in post-processing to screen out invalid responses from the data set. Therefore, if a respondent indicated that they had used shared ride-hailing services in the past month during the pandemic, they were removed from the data. The survey concluded with common demographic questions to collect background information about each respondent including age, race, gender, education, income, and employment status.

4.2.1. Data Collection

The data was collected through the use of an online survey hosted by the Qualtrics platform. Data collection began on October 14, 2020, and concluded on November 18, 2020. This data collection period was chosen due to the relative stability of virus cases and return from lockdown restrictions in Georgia (May 2020). Before the data collection period, new reported COVID-19 cases in the metro Atlanta area had peaked and were declining until mid-October. During the period of data collection, the Atlanta metro area had a slight increase in new COVID-19 cases but no change in restrictions. Additionally, COVID-19 vaccines were still in developmental phases, but many were optimistic about upcoming vaccines by the end of October. Data reporting the effectiveness of COVID vaccines was released in mid-November 2020 and the FDA issued emergency use authorization in December 2020.

Survey data was collected through multiple online recruitment channels from adults in the Atlanta metro area. Additional discussion of the survey's recruitment methodology can be found in Chapter 3. Our mixed sampling approach included participants recruited through the following five survey methods:

a) *Online opinion panel service (n=384):* A commercial online opinion panel was used to recruit and verify a specific number of guaranteed and timely responses. A total number of 384 valid surveys included in the data set were recruited through this channel.

b) *Email recontact of respondents from past transportation surveys (n=211)*: A total of 1447 email survey requests were sent to the email addresses provided by willing respondents in previous transportation studies. Of the email recontacts, 1185 were from a two-wave bicyclist preferences survey that targeted Westside, Eastside, Grant Park, and South Atlanta neighborhoods in 2017 and 2019 [19]. The other 262 email recontacts were from an intercept survey of MARTA riders after the I-85 road closure in 2017. A total of 211 valid respondents completed the survey through this channel (14.6% valid response rate). The low response rate was possibly due to the large gap in time between survey requests and the lack of monetary incentive.

c) *Neighborhood newsletters and platforms (n=132):* Survey distribution requests were sent to 58 neighborhood planning units and neighborhood organizations in the metro-Atlanta area. Twelve organizations agreed to share the survey within their community through online newsletters, email groups, and/or social media like Facebook and Nextdoor. This effort resulted in a total of 132 valid survey responses completed through this channel.

d) *Facebook advertisements (n=46):* A Facebook advertisement campaign linking directly to the survey ran during the full data collection period. The audience for this campaign included adults in the Atlanta area. The campaign, which included visual media ads and call-to-action text linking directly to the survey site, generated 565 unique link clicks and ultimately resulted in 90 completed surveys. Only 46 of these attempts were valid responses included in the data. This low valid response rate (8.1%) was possibly due to the lack of monetary incentive for respondents or survey fatigue.

e) *Task distribution platform (n=14):* Mechanical Turk (MTurk), a task distribution platform where requesters post simple paid tasks such as surveys, was used to recruit respondents. Over the data collection period, the survey task was published twelve times. To participate in the survey task and receive the $2 incentive upon completion, MTurk-registered workers who lived in Georgia had to answer a screener question to specify that they live or work in the Atlanta area. This recruitment channel only resulted in 14 valid responses. This low response volume may be due to the limited number of Atlanta residents active on the platform.

4.2.2. Data Description

The data collection process resulted in a sample of 787 complete and valid surveys. The sample over-represents highly-educated, high-income, middle-aged, and white populations, as displayed in Table 4-1 which compared the survey results with the ACS demographic estimates of the Atlanta population.

TABLE 4-1: DISTRIBUTION OF SURVEY RESPONDENTS DEMOGRAPHICS

		Responses (n=787)	% of Respondents	% of Atlanta Population*
Household Income	Less than $25,000	67	8.7%	14.7%
	$25,00 - $49,999	112	14.1%	19.2%
	$50,00 - $74,999	110	14.2%	18.2%
	$75,00 - $99,999	100	12.7%	13.2%
	$100,000 - $149,999	174	22.1%	16.8%
	More than $150,000	223	28.2%	17.8%
Gender	Female	429	54.4%	51.7%
	Male	355	45.2%	48.3%
	Prefer to Self-Describe	3	0.4%	NA
Respondent Age	18-34	211	26.8%	31.8%
	35-49	332	42.2%	27.8%
	50-64	172	21.9%	24.8%
	65+	72	9.1%	16.7%

TABLE 4-2: CONTINUED

		Responses (n=787)	% of Respondents	% of Atlanta Population*
Race/Ethnicity**	White / Caucasian	568	71.4%	45.9%
	Black / African American	175	22%	34.2%
	Hispanic / Latino	38	4.8%	11.0%
	American Indian / Native American	12	1.5%	0.2%
	Asian / Pacific Islander	41	5.2%	6.1%
	Other	25	3.1%	2.7%
Education	Lower than bachelor's degree	157	19.9%	60.1%
	Bachelor's degree or higher	630	80.1%	39.9%

*From 2019 ACS estimates
** Respondents were allowed to mark more than one (sum of percentages may exceed 100%)

A further breakdown of the demographic categories used in the models can be found in Table 4-2. Age and income were further broken down into different groupings, which indicate a large percentage of the sample (40.0%) was Gen X, 41-55 years old. The frequencies of trip usage by different modes before the pandemic were used to identify non-users, occasional users, and active users for ride-hailing, shared ride-hailing, and transit. Non-users indicated that they "Never" used the mode before the pandemic, occasional users indicated that they used the mode "1-3 times a month" or "less than once a month", and active users indicated that they used the mode at least once a week. The majority of respondents that used transit and private ride-hailing were occasional users (56.8% and 66.1%). Active shared ride-hailing users only accounted for a small share of respondents (7.8%) and were mainly represented by Millennials (25-40 yrs. old) and Gen Z (18-24 yrs. old) participants. Almost half of the respondents (49.6%) had never used shared ride-hailing. A multimodal lifestyle binomial variable was determined by the usage of a bicycle, shared e-scooter, transit, or ride-hailing at least once a week. Multimodal respondents made up 35.7% of the sample.

The survey included two questions asking the participant's employment situation before and during the pandemic. These answers were compared and a binomial variable indicated an employment change resulting in less work or study. The majority of the sample before and during the pandemic only worked (79.0% and 72.9%). The pandemic resulted in an employment situation with less work or studying for 7.9% of the respondents.

TABLE 4-3: ADDITIONAL DEMOGRAPHICS AND LIFESTYLE INDICATORS OF SAMPLE

Demographics and Lifestyle Indicator		Responses (n=787)	% of Respondents
Generation	Gen Z (18-24 yrs. old)	52	6.6%
	Millennial (25-40 yrs. old)	257	32.7%
	Gen X (41-55 yrs. old)	315	40.0%
	Boomer (56-74 yrs. old)	153	19.4%
	Silent (75+ yrs. old)	10	1.3%
Lower than $50K Income		179	22.8%
Higher than $100K Income		397	50.40%

TABLE 4-4: CONTINUED

Demographics and Lifestyle Indicator		Responses (n=787)	% of Respondents
Private Ride-Hailing Use (Pre-COVID-19)	Non-User	107	13.6%
	Occasional User	520	66.1%
	Active User	160	20.3%
Shared Ride-Hailing Use (Pre-COVID-19)	Non-User	390	49.6%
	Occasional User	336	42.6%
	Active User	61	7.8%
Transit Use (Pre-COVID-19)	Non-User	178	22.6%
	Occasional User	447	56.8%
	Active User	162	20.6%
Multimodal Lifestyle		281	35.7%
Employment (Pre-COVID)	Does not work or study	98	12.5%
	Only studies	45	5.7%
	Only works	622	79.0%
	Works and studies	22	2.8%
Employment (October 2020)	Does not work or study	150	19.1%
	Only studies	41	5.2%
	Only works	571	72.9%
	Works and studies	22	2.8%
Employment change resulting in less work or study		62	7.9%

4.3.2.1. Personal Attitude and Opinion Results

Participants responded to 23 attitudinal and opinion statements on a five-point Likert-scale from “Strongly Disagree” to “Strongly Agree”. These statements were designed so that several related statements would pertain to a single construct for future factor analysis. The average, standard deviation, and median response to selected personal attitude and opinion questions (coded from 1 = Strongly Disagree to 5 = Strongly Agree) were calculated, as displayed in Table 4-3. Attitudinal statements revealed that the majority of the sample consider themselves to be sociable (82.5%), would choose to work from home if given the option (67.2%), missed small interactions with strangers (61.0%), and always carried hand sanitizer (58.6%).

TABLE 4-5: RESPONSE TO SELECTED PERSONAL ATTITUDE AND OPINION QUESTIONS

	Mean	S.D.	Median
If I could commute and go into work, I would go to my office.	2.79	1.26	3
If I could work from home and not commute, I would work from home.	3.83	1.20	4
I travel more now simply to “get out” instead of traveling for a reason.	2.87	1.29	3
I enjoy chatting with fellow passengers in a shared ride-hailing vehicle.	2.89	1.11	3
I wear headphones while in a ridesharing vehicle to avoid interactions.	2.45	1.21	2
I enjoy chatting with my ride-hailing driver.	3.33	1.09	3
I miss small interactions with strangers.	3.59	1.09	4
I always carry hand sanitizer.	3.47	1.33	4
I’m uncomfortable being around people I don’t know.	3.04	1.13	3
My friends and family would describe me as “germ conscious”.	3.33	1.08	3
I consider myself to be a sociable person.	4.11	0.86	4
1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree			

In October 2020, COVID-19 protocols on public transit included requiring drivers to wear masks, encouraging passengers to wear masks and social distance, and providing frequent cleaning and sanitizing of stations and vehicles. We asked respondents their opinion on these procedures through Likert-scale opinion statements and found the average respondents supported most protocols, as seen in Table 4-4. The majority of respondents (95.4%) agreed that wearing a mask should be required for all passengers riding public transit. The majority of respondents (67.9%) would have felt uncomfortable due to potential COVID-19 risk if someone sat next to them on a MARTA bus or train, even if they were wearing a mask. Almost half (46.0%) of respondents trusted the precautions and extra effort taken by MARTA transit to clean and sanitize. To balance the extra resources dedicated to COVID-19 procedures in transit and reduce risk, some bus routes were suspended. This response from transit agencies did not reflect the opinion of respondents as the majority of respondents (68.6%) disagreed that transit services should have been suspended until a vaccine for COVID-19 was found.

Table 4-6: Response to Selected Transit COVID-19 Measures Questions (n=787)

	Mean	S.D.	Median
Transit services should be suspended until a vaccine for COVID-19 is found.	2.25	1.15	2
I trust the precautions and extra effort taken by MARTA transit to clean and sanitize.	3.34	1.07	3
Opening the windows while riding on public transit is worth the discomfort.	3.92	1.00	4
If someone wearing a mask sat next to me on MARTA, I would feel uncomfortable.	3.76	1.15	4
Wearing a mask should be required for all passengers riding public transit.	4.78	0.61	5
1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree			

COVID-19 protocols on ride-hailing vehicles included suspending pooled services, requiring passengers and drivers to wear masks, opening the window if applicable, and providing passengers with extra sanitation options. We asked respondents their opinion on these procedures through Likert-scale opinion statements and found the average respondent supported these protocols, as seen in Table 4-5. Almost half of the respondents (43.4%) agreed that shared ride-hailing services should have been suspended until a vaccine for COVID-19 was found. Nearly three-quarters of respondents (73.7%) agreed that if their ride-hailing driver wasn't wearing a mask, they would have requested a new vehicle. Nearly four-fifths of respondents (78.6%) agreed that opening the windows while riding on a ride-hailing vehicle was worth the discomfort as it reduces the risk of COVID-19. Half of the respondents (53.4%) agreed that they would have felt comfortable using a ride-hailing vehicle if they were equipped with disinfectant sprays and wipes to sanitize the vehicle before and after each ride.

TABLE 4-7: RESPONSE TO SELECTED RIDE-HAILING COVID-19 MEASURES QUESTIONS (N=787)

	Mean	S.D.	Median
Opening the windows while riding in a ride-hailing vehicle is worth the discomfort as it reduces the risk of COVID-19.	4.10	0.99	4
If my ride-hailing driver wasn't wearing a mask, I would request a new vehicle.	3.99	1.06	4
I would feel comfortable riding with a stranger in a shared ride-hailing vehicle as long as there is a seat in between passengers.	2.53	1.25	2
Shared ride-hailing with strangers services should be suspended until a vaccine for COVID-19 is found.	3.13	1.25	3
I would feel comfortable using a ride-hailing vehicle if I was equipped with disinfectant sprays and wipes to sanitize the vehicle before and after each ride	3.37	1.20	4

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree

The attitudinal and opinion questions in the second section of the survey were designed to be able to use several items to form aspects of a single construct. A set of underlying factors can explain the interrelationships among observed attitude and opinion variables. To construct the underlying factors, a Kaiser-Mayer-Olkin (KMO) measure was used to check the sampling adequacy. The data resulted in a KMO statistic equal to 0.701 showing that factor analysis could be performed on the attitude and opinion data. The data from these sections consisted of 18 five-point Likert-scale ordinal variables. Because the variables were in the ordinal form, a polychoric correlation was performed. The varimax orthogonal rotation technique, which maximized the variance of squared factor loadings, was used to improve interpretability. Exploratory factor analysis solutions with 3 to 6 factors were considered. Items with weak loadings and poor interpretability were considered for removal. As seen in Table 4-6, the final (rotated) factor loading matrix, with factor loadings higher than 0.3 shown and values higher than 0.6 in bold, the factor analysis yielded a four-factor solution which explained 55.54% of the variance. The four identified factors based on the loadings are explained below:

- *Follow Safety Measures*: The four variables positively related to wearing masks and improving air circulation in shared mobility modes form this factor.
- *Extrovert:* Four variables related to positively interacting with other people combine to form this factor.
- *Trust Precautions:* Three variables relate to the comfort and trust of shared mobility COVID precautions.
- *Germophobe:* Three variables relate to the awareness of germs spreading.

Table 4-8: Factor Loading Matrix of 4 Factors on 14 Items

	Follow Safety Measure	Extrovert	Trust Precautions	Germophobe
Opening the windows while riding on public transit is worth the discomfort as it reduces the risk of COVID-19.	**0.771**			
If my ride-hailing driver wasn't wearing a mask, I would request a new vehicle.	**0.733**			
Opening the windows while riding in a ride-hailing vehicle is worth the discomfort as it reduces the risk of COVID-19.	**0.726**			
Wearing a mask should be required for all passengers riding public transit.	**0.646**			
I enjoy chatting with my ride-hailing driver.		**0.807**		
I enjoy chatting with fellow passengers in a shared ride-hailing vehicle (e.g. UberPool).		**0.721**		
I miss small interactions with strangers.		**0.717**		
I consider myself to be a sociable person.		**0.608**		
I would feel comfortable riding in a shared ride-hailing vehicle as long as there is a seat in between passengers.			**0.818**	
I would feel comfortable using a ride-hailing vehicle if I was equipped with disinfectant sprays and wipes to sanitize the vehicle before and after each ride.			**0.697**	
I trust the precautions and extra effort taken by MARTA transit to clean and sanitize.			**0.667**	
I always carry hand sanitizer.				**0.783**
My friends and family would describe me as "germ conscious".				**0.762**
If someone wearing a mask sat next to me on a bus or train, I would feel uncomfortable due to COVID-19 risk.			-0.353	0.408
Values lower than 0.3 in magnitude were suppressed for ease of interpretation.				

4.3.2.2. Usage of Ride-Hailing, Shared Ride-Hailing, and Transit Results

In addition to reported preferences, the survey examined revealed preference data by collecting the actual ridership frequency for each shared mobility mode before and during the COVID-19 pandemic. Two consecutive sets of survey questions (one before the pandemic and one in the past month during the pandemic) asked respondents to select a usage frequency category for each mode, which were converted into the approximate monthly frequencies shown in parentheses:

- Never (0)
- Less than once a month (0.5)
- 1-3 times a month (2)
- 1-2 times a week (6)
- 3-4 times a week (14)
- 5 or more times a week (25)

In addition to shared mobility modes, the survey asked for usage of typical mode choices and technologies that replace trips. Each choice before the pandemic and in October 2020 was converted to its monthly frequency equivalent and the average and standard deviation of the sample was calculated, as displayed in Table 4-7. The percent of respondents actively, occasionally, and not using the mode during each period was also displayed in Table 4-7; active usage represented use of a mode at least once a week, occasional usage represented use a few times a month, and non-usage represented no use. Additionally, the before COVID-19 usage measure was subtracted from the October 2020 usage measure to determine the change in usage, as seen in Table 4-7. The transportation mode with the highest frequency of usage among respondents before the pandemic and in October 2020 were personal vehicles and walking. The average monthly-frequency usage of all modes decreased during the pandemic, with the largest negative change occurring in personal vehicles. Of the shared modes, the monthly frequency usage decreased the most in rail transit. The usage frequency of teleworking, as a means of trip replacement, increased by an average of 7.14 additional days per month between the pre-COVID period and October 2020.

TABLE 4-9: MONTHLY FREQUENCY OF MODAL USAGE BEFORE, DURING, AND CHANGE DUE TO

	Sample Average Usage (S.D)	% of Active Usage	% of Occasional Usage	% of Non-Usage	Average Change in Usage (S.D.)
Private Vehicle (Single Occupant)					
Before COVID	16.51 (10.05)	80.56	12.58	6.86	-4.40 (9.75)
Fall 2020	12.11(9.65)	74.21	18.17	7.62	
Private Vehicle (Multiple Occupants)					
Before COVID	8.54 (8.47)	60.74	30.88	8.39	-3.52 (7.32)
Fall 2020	5.02 (6.87)	40.53	37.87	21.60	
Private Ride-Hailing					
Before COVID	2.84 (4.68)	20.33	66.07	13.60	-1.95 (4.46)
Fall 2020	0.89 (3.03)	5.21	28.21	66.58	
Shared Ride-Hailing					
Before COVID	1.19 (3.15)	7.75	42.69	49.56	-1.13 (3.11)
Fall 2020	0.00 (0.00)	0.00	0.00	100.00	
MARTA Bus					
Before COVID	2.05 (5.36)	12.96	32.78	54.36	-1.37 (4.89)
Fall 2020	0.68 (3.22)	4.32	10.17	85.51	
MARTA Rail					
Before COVID	3.14 (6.56)	17.03	57.31	25.67	-2.37 (5.95)
Fall 2020	0.77 (3.16)	4.70	15.25	80.05	
Transit					
Before COVID	3.60 (6.93)	20.58	56.80	22.62	-2.65 (6.32)
Fall 2020	0.96 (3.69)	5.84	15.63	78.53	
Walk					
Before COVID	11.06 (10.23)	61.25	27.95	10.80	-1.10 (7.23)
Fall 2020	9.96 (9.73)	60.74	22.24	17.03	
Bicycle					
Before COVID	2.60 (6.03)	16.39	26.43	57.18	-0.50 (4.32)
Fall 2020	2.09 (5.35)	14.23	17.66	68.11	
E-Scooter					
Before COVID	0.29 (1.83)	2.41	19.57	78.02	-0.12 (2.02)
Fall 2020	1.16 (0.61)	2.41	6.23	91.36	
Telework					
Before COVID	3.80 (7.18)	44.98	28.97	26.05	7.14 (10.66)
Fall 2020	10.94 (11.28)	52.86	14.36	32.78	
Online Shopping					
Before COVID	5.17 (6.55)	38.88	55.02	6.10	1.85 (6.09)
Fall 2020	7.02 (7.43)	54.51	39.77	5.72	
Food Delivery					
Before COVID	3.06 (5.47)	23.76	43.84	32.40	1.30 (5.09)
Fall 2020	4.36 (6.41)	35.32	35.45	29.22	
Video Chat					
Before COVID	3.70 (6.84)	24.28	37.61	38.12	4.26 (7.01)
Fall 2020	7.96 (8.76)	54.26	32.15	13.60	

Never (0), Less than once a month (0.5), 1-3 times a month (2), 1-2 times a week (6), 3-4 times a week (14), 5 or more times a week (25)

These initial findings were limited due to the small sample of respondents actively using the other shared modes in the period before the pandemic. To account for the large number of shared mobility non-users in the sample, the change in usage frequency was further broken down by pre-COVID "user type" as Table 4-8, with the sample means indicated by $\bar{Y}_1$ for the pre-COVID period and $\bar{Y}_2$ for the October 2020 period. Occasional and active users of shared modes reported mostly decreases in modal usage while most non-users did not change their shared mode usage. A small portion of the sample increased usage of transit and private ride-hailing. For example, only 4% of occasional users reported an increase in usage frequency of transit. Similarly, only 4% of occasional and active users of private ride-hailing reported increases in their usage frequency.

TABLE 4-10: CHANGES IN USAGE OF SHARED MODE (BEFORE TO DURING THE PANDEMIC IN OCTOBER 2020)

Private Ride-Hailing Change in Usage *($\bar{Y}_1$=2.84, $\bar{Y}_2$=0.89, n=787)*			
	Non-User *($\bar{Y}_1$=0.00, $\bar{Y}_2$=0.35, n=107)*	***Occasional User*** *($\bar{Y}_1$=0.43, $\bar{Y}_2$=1.25, n=520)*	***Active User*** *($\bar{Y}_1$=9.93, $\bar{Y}_2$=2.73, n=160)*
Decreasing	0 (0%)	222 (43%)	138 (86%)
No Change	104 (97%)	275 (53%)	16 (10%)
Increasing	3 (3%)	23 (4%)	6 (4%)
Shared Ride-Hailing Change in Usage *($\bar{Y}_1$=1.19, $\bar{Y}_2$=0.00, n=787)*			
	Non-User *($\bar{Y}_1$=0.00, $\bar{Y}_2$=0.00, n=390)*	***Occasional User*** *($\bar{Y}_1$=0.98, $\bar{Y}_2$=0.00, n=336)*	***Active User*** *($\bar{Y}_1$=9.89, $\bar{Y}_2$=0.00, n= 61)*
Decreasing	0 (0%)	336 (100%)	61 (100%)
No Change	390 (100%)	0 (0%)	0 (0%)
Increasing	0 (0%)	0 (0%)	0 (0%)
Transit Change in Usage *($\bar{Y}_1$=3.60, $\bar{Y}_2$=0.96, n=787)*			
	Non-User *($\bar{Y}_1$=0.00, $\bar{Y}_2$=0.00, n=178)*	***Occasional User*** *($\bar{Y}_1$=0.95, $\bar{Y}_2$=0.48, n=447)*	***Active User*** *($\bar{Y}_1$=14.88, $\bar{Y}_2$=3.30, n=162)*
Decreasing	0 (0%)	106 (24%)	139 (86%)
No Change	178 (100%)	323 (72%)	23 (14%)
Increasing	0 (0%)	18 (4%)	0 (0%)
μ_1= average Pre-COVID and μ_2=average October 2020			

To understand the reason behind the change in transit and shared ride-hailing usage, follow-up questions were asked, as displayed in Table 4-9. Of the 263 respondents that indicated a change in usage of transit, 188 (71.5%) agreed that the change was due to a change in transit service. The most common reason for change in transit service included bus routes no longer in service (31.4%) and bus routes with less frequent service (26.1%). A sizable minority (40.8%) of respondents that indicated a change in usage of shared ride-hailing (n=397) agreed that the change was due to shared ride-hailing being unavailable.

TABLE 4-11: REASONS EXPLAINING CHANGE IN TRANSIT AND SHARED RIDE-HAILING USAGE

	Frequency	Percentage
I have changed the way I travel because my typical transit service has changed;	188	23.9%*
My bus route is no longer in service.	59	31.4%**
My bus route has more frequent service.	26	13.8%**
My bus route has less frequent service.	49	26.1%**
My rail service has less frequent service.	28	14.9%**
I traveled more on the bus because it was free.	26	13.8%**
I have changed the way I travel because shared ride-hailing is not available.	162	20.6%*

* Percentage of full sample (n = 787).
** Percentage of users giving this reason, among those who changed the way they travel because their typical transit service had changed (n=188).
(Respondents were allowed to select more than one reason)

4.3.2.3. Level of Comfort Using Ride-hailing, Shared Ride-hailing, and Transit Results

To understand changes in comfort levels using different modes of transportation throughout the pandemic, respondents were asked three questions about private ride-hailing, shared ride-hailing with strangers, and public transit for each specified period:

- “Before COVID-19, I would have felt comfortable using...”,
- “With the current COVID-19 risk, I would feel comfortable using ...”
- “In the future when a COVID-19 vaccine is available, I will feel comfortable using...”

To capture the comfort level of shared mobility after the pandemic, the future period was defined as the time when a vaccine is available. As the definition of the time “after the pandemic” could vary among individuals (e.g. when positive cases have been significantly reduced, when most restrictions have been lifted, when a “cure” is introduced…) a fixed future period was selected to increase specificity and represent an attainable, forthcoming “new normal” period.

For each shared mode and period, respondents indicated their level of comfort with a 5-point Likert-scale from “Strongly Agree” to “Strongly Disagree”, as displayed in Figure 4-2.

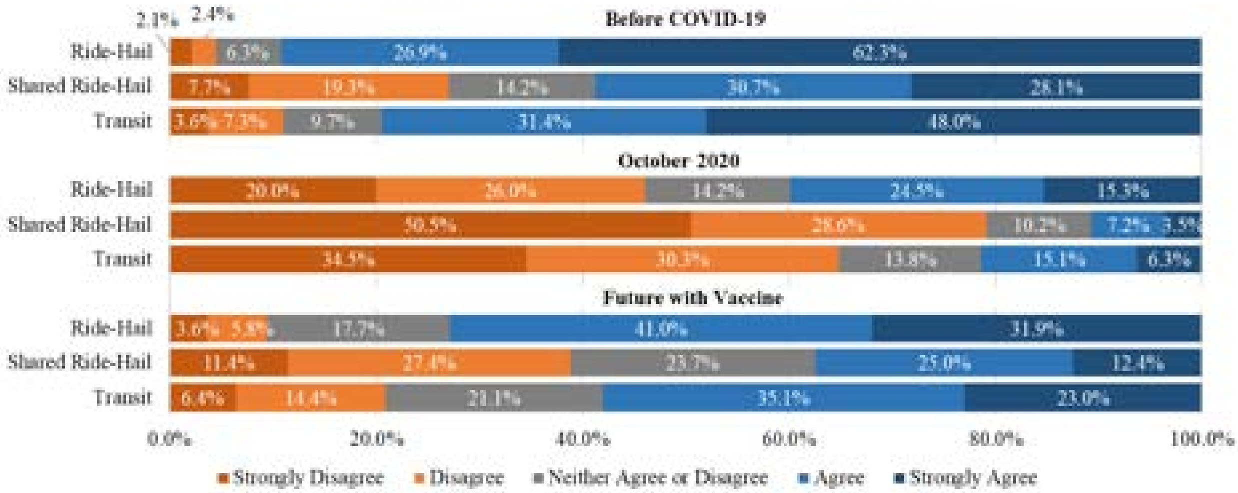


FIGURE 4-2: DISTRIBUTION OF AGREEMENT WITH "I WOULD HAVE FELT COMFORTABLE USING..." FOR SHARED MODES (N=787)

The majority of respondents reported that they felt comfortable using ride-hailing (89.3% agreed or strongly agreed), transit (79.8%), and shared ride-hailing (58.7%) before the pandemic. Shared ride-hailing services had the lowest level of comfort, with only 28.1% of respondents *strongly* agreeing that they felt comfortable using the service before COVID-19. Assuming the October 2020 risk of COVID-19, the majority of respondents did not feel comfortable (disagreed or strongly disagreed) using shared ride-hailing (80.0%) and transit (65.4%) while almost half of respondents (46.4%) indicated that they did not feel comfortable using private ride-hailing. In October 2020, more respondents reported that they would feel comfortable (agreed or strongly agreed) using private ride-hailing (39.5%) than transit (21.4%) or shared ride-hailing (10.7%). A majority of respondents indicated that they would feel comfortable (agreed or strongly agreed) using ride-hailing (72.3%) and transit (58.2%) in the future when a vaccine became available. Only 37.4% of respondents reported that they would feel comfortable (agreed or strongly agreed) using shared ride-hailing in the future when a vaccine became available.

Assigning a number from 1 to 5 for each category of the Likert scale (1=Strongly Disagree to 5 = Strongly Agree), we examined the ordinal level of comfort data, as displayed in Table 4-10a – Table 4-10c. A value closer to 5 represented a strong level of comfort and a value closer to 1 represented a low level of comfort. These tables also displayed results from paired two-sample t-tests with unequal variances which were performed to test the null hypothesis that the mean difference between the sets of observations (before to current, before to future, and current to future) was zero. The strongly significant rejection of all null hypotheses indicated that the sample had a change in the level of comfort between all periods for all user types. The general sample indicated that shared mobility reported levels of comfort would return to slightly lower levels of comfort in the future when a vaccine became available compared to pre-COVID-19 levels; the average change in level of comfort with shared mobility between pre-COVID and "future" vaccine was around -0.55. Active users were more comfortable than occasional and non-users in all modes and across all periods. In October 2020, the average comfort levels across usage types were the most similar to each other; active users reported an average level of comfort of only 0.66, 0.57, 0.68 higher than non-users and 0.32, 0.21, 0.26 higher than occasional users for private ride-hail, shared ride-hail, and transit respectively.

TABLE 4-12: COMFORT LEVEL FOR MODE BY TIME PERIOD AND USER GROUP

TABLE 4-10A: COMFORT LEVEL FOR PRIVATE RIDE-HAIL BY TIME PERIOD AND USER GROUP

"I would have felt comfortable using..." Private Ride-Hail					
		Total (n=787)	Non-User (n=107)	Occasional User (n=520)	Active User (n=160)
Median	Before COVID-19	5	4	5	5
	Current (October 2020)	3	2	3	4
	Future When a Vaccine is Available	4	3	4	4
Mean	Before COVID-19	4.45	3.54	4.59	4.59
	Current (October 2020)	2.88	2.52	2.86	3.18
	Future When a Vaccine is Available	3.92	3.21	3.97	4.20
Variance	Before COVID-19	0.77	1.55	0.48	0.57
	Current (October 2020)	1.91	1.78	1.81	2.15
	Future When a Vaccine is Available	1.04	1.55	0.87	0.89
Average Change in Level of Comfort	Before → Current	-1.57***	-1.02***	-1.73***	-1.41***
	Current → Future	1.04***	0.69***	1.11***	1.02***
	Before → Future	-0.53***	-0.33**	-0.62***	-0.39***

Paired Two-Sample t-tests Comparing Means of Two Periods: *** p-value < 0.001, ** p-value <0.01, * p-value < 0.05
1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree

TABLE 4-10B: COMFORT LEVEL FOR PRIVATE RIDE-HAIL BY TIME PERIOD AND USER GROUP

"I would have felt comfortable using..." Shared Ride-Hail					
		Total (n=787)	Non-User (n=390)	Occasional User (n=336)	Active User (n=61)
Median	Before COVID-19	4	3	4	5
	Current (October 2020)	1	1	2	2
	Future When a Vaccine is Available	3	2	4	4
Mean	Before COVID-19	3.52	2.88	4.13	4.26
	Current (October 2020)	1.83	1.63	1.99	2.20
	Future When a Vaccine is Available	2.99	2.53	3.40	3.63
Variance	Before COVID-19	1.67	1.63	0.90	0.96
	Current (October 2020)	1.17	0.88	1.40	1.29
	Future When a Vaccine is Available	1.48	1.25	1.27	1.51
Average Change in Level of Comfort	Before → Current	-1.69***	-1.25***	-2.14***	-2.06***
	Current → Future	1.16***	0.90***	1.41***	1.43***
	Before → Future	-0.53***	-0.35***	-0.73***	-0.63**

Paired Two-Sample t-tests Comparing Means of Two Periods: *** p-value < 0.001, ** p-value <0.01, * p-value < 0.05
1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree

TABLE 4-10C: COMFORT LEVEL FOR PRIVATE RIDE-HAIL BY TIME PERIOD AND USER GROUP

"I would have felt comfortable using..." Transit					
		Total (n=787)	Non-User (n=178)	Occasional User (n=447)	Active User (n=162)
Median	Before COVID-19	4	3	5	5
	Current (October 2020)	2	2	2	2
	Future When a Vaccine is Available	4	3	4	4
Mean	Before COVID-19	4.13	3.26	4.35	4.50
	Current (October 2020)	2.27	1.89	2.31	2.27
	Future When a Vaccine is Available	3.54	2.78	3.73	3.85
Variance	Before COVID-19	1.18	0.72	0.76	0.79
	Current (October 2020)	1.56	1.48	1.57	1.54
	Future When a Vaccine is Available	1.39	1.02	1.09	1.25
Average Change in Level of Comfort	Before → Current	-1.86***	-1.37***	-2.04***	-1.93***
	Current → Future	1.27***	0.89***	1.42***	1.28***
	Before → Future	-0.59***	-0.48***	-0.62***	-0.65***

Paired Two-Sample t-tests Comparing Means of Two Periods: *** p-value < 0.001, ** p-value <0.01, * p-value < 0.05
1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree

4.3.2.4. Change in Level of Comfort Using Shared Mobility Results

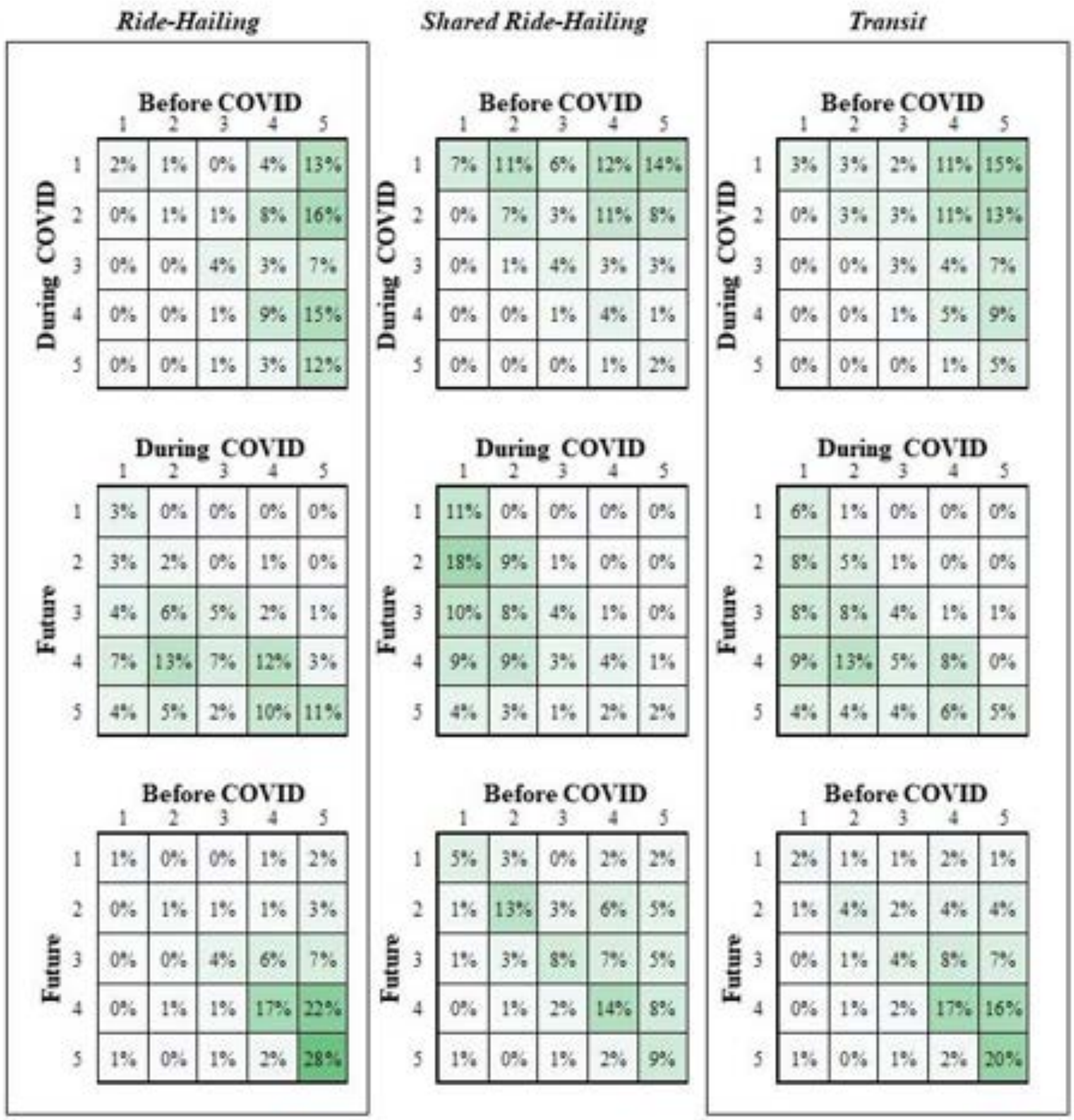
Examining the frequency of changes in reported comfort between periods, as seen in Table 4-11, we can see a significant decrease in comfort for all modes between the current period and before the pandemic. Respondents indicated that their level of comfort will increase for all modes when comparing the current and future comfort levels. This suggests their current level of comfort using shared mobility was lower than it was before the pandemic and will increase in the future after the pandemic. Comparing the reported level of comfort in the periods before and after the pandemic, most respondents indicated no change or a decrease in comfort across all modes. If this trend of lower reported level of comfort in shared modes persists, future ridership may not return to pre-pandemic levels for an extended period of time.

TABLE 4-13: FREQUENCY OF CHANGES IN COMFORT BETWEEN TIME PERIODS

Change in Reported Comfort		Decrease		No Change		Increase	
Before to Current (n=787)	Private Ride-hail	540	68.6%	209	26.6%	38	4.8%
	Shared Ride-hail	568	72.2%	190	24.1%	29	3.7%
	Transit	612	77.8%	150	19.1%	25	3.2%
Current to Future (n=787)	Private Ride-hail	52	6.6%	268	34.1%	467	59.3%
	Shared Ride-hail	30	3.8%	234	29.7%	523	66.5%
	Transit	30	3.8%	216	27.4%	541	68.7%
Before to Future (n=787)	Private Ride-hail	336	42.7%	401	51.0%	50	6.4%
	Shared Ride-hail	313	39.8%	386	49.0%	88	11.2%
	Transit	355	45.1%	369	46.9%	63	8.0%

Crosstabulations of reported comfort levels for each pair of time periods were created to further visualize these shifts, as seen in Figure 4-3. These highlight the different patterns in reported level of comfort among modes from 1 (strongly disagree) to 5 (strongly agree). These figures illustrate the similarities between changes in comfort in transit and shared ride-hailing due to the pandemic. Individual shifts in level of reported comfort were calculated between periods for each mode. The distribution of change in comfort ranges from -4 to 4 as displayed in Figure 4-4. The largest frequencies of negative changes occurred at the start of the pandemic, positive changes occurred as the pandemic continues, and no changes occurred long-term due to the pandemic. It is important to note that the same change in comfort can result from two different starting points.

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree/Disagree, 4=Agree, 5=Strongly Agree



Ride-Hailing

During COVID \ Before COVID	1	2	3	4	5
1	2%	1%	0%	4%	13%
2	0%	1%	1%	8%	16%
3	0%	0%	4%	3%	7%
4	0%	0%	1%	9%	15%
5	0%	0%	1%	3%	12%

Future \ During COVID	1	2	3	4	5
1	3%	0%	0%	0%	0%
2	3%	2%	0%	1%	0%
3	4%	6%	5%	2%	1%
4	7%	13%	7%	12%	3%
5	4%	5%	2%	10%	11%

Future \ Before COVID	1	2	3	4	5
1	1%	0%	0%	1%	2%
2	0%	1%	1%	1%	3%
3	0%	0%	4%	6%	7%
4	0%	1%	1%	17%	22%
5	1%	0%	1%	2%	28%

Shared Ride-Hailing

During COVID \ Before COVID	1	2	3	4	5
1	7%	11%	6%	12%	14%
2	0%	7%	3%	11%	8%
3	0%	1%	4%	3%	3%
4	0%	0%	1%	4%	1%
5	0%	0%	0%	1%	2%

Future \ During COVID	1	2	3	4	5
1	11%	0%	0%	0%	0%
2	18%	9%	1%	0%	0%
3	10%	8%	4%	1%	0%
4	9%	9%	3%	4%	1%
5	4%	3%	1%	2%	2%

Future \ Before COVID	1	2	3	4	5
1	5%	3%	0%	2%	2%
2	1%	13%	3%	6%	5%
3	1%	3%	8%	7%	5%
4	0%	1%	2%	14%	8%
5	1%	0%	1%	2%	9%

Transit

During COVID \ Before COVID	1	2	3	4	5
1	3%	3%	2%	11%	15%
2	0%	3%	3%	11%	13%
3	0%	0%	3%	4%	7%
4	0%	0%	1%	5%	9%
5	0%	0%	0%	1%	5%

Future \ During COVID	1	2	3	4	5
1	6%	1%	0%	0%	0%
2	8%	5%	1%	0%	0%
3	8%	8%	4%	1%	1%
4	9%	13%	5%	8%	0%
5	4%	4%	4%	6%	5%

Future \ Before COVID	1	2	3	4	5
1	2%	1%	1%	2%	1%
2	1%	4%	2%	4%	4%
3	0%	1%	4%	8%	7%
4	0%	1%	2%	17%	16%
5	1%	0%	1%	2%	20%

FIGURE 4-3: CROSSTABULATIONS OF COMFORT LEVELS IN SHARED MODES FOR PAIRS OF TIME PERIODS (N=787)

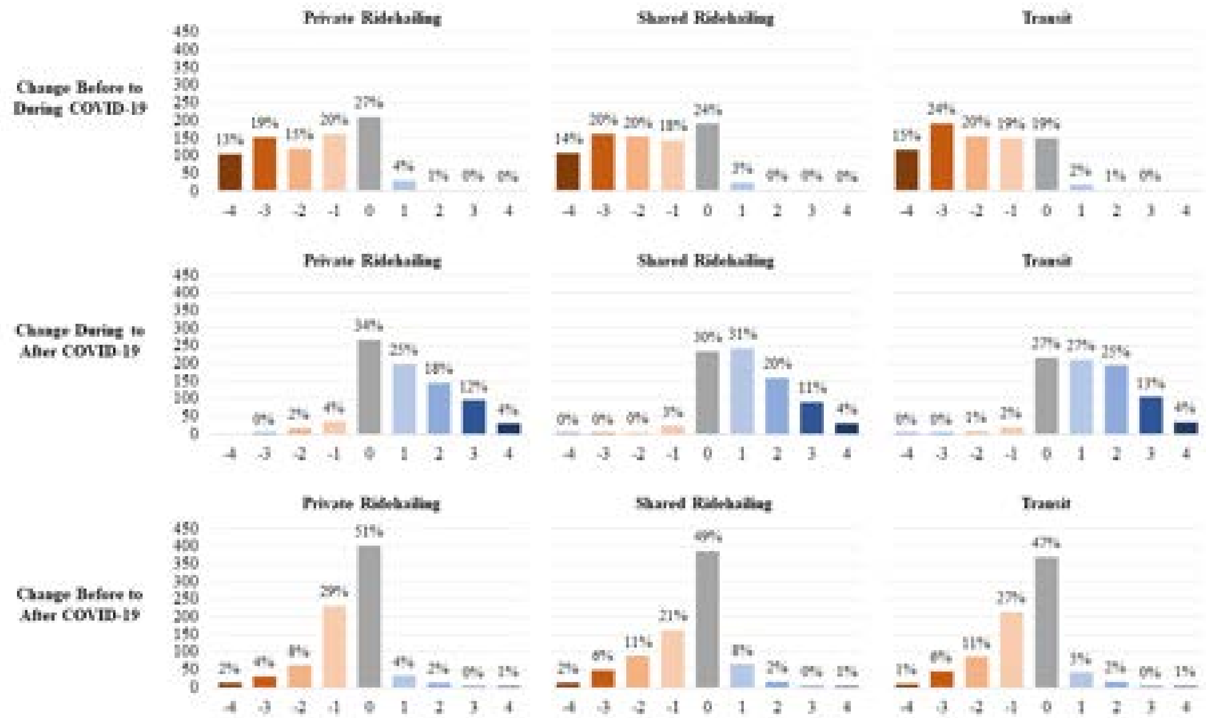


FIGURE 4-4: DISTRIBUTION OF CHANGE IN COMFORT LEVEL FOR RIDE-HAILING, SHARED RIDE-HAILING, AND TRANSIT (N=787)

4.3.3. Shared Mobility Comfort Models Methodological Approach

One of the objectives of this study was to investigate how factors of individuals' willingness to share mobility were impacted by the COVID-19 pandemic. A regression analysis allowed us to understand the impact of explanatory variables on the level of comfort with using shared mobility during three periods during the pandemic. For each period (before the pandemic, October 2020 during the pandemic, and a hypothetical future with a vaccine), reported level of comfort models were built with dependent variables as level of comfort in private ride-hailing, shared ride-hailing, and transit. Independent variables in the models included attitudinal factor scores calculated from the factor analysis, socio-demographic binomial and numeric variables, and prior modal usage binomial variables across different modes. As the dependent variables were Likert-type data with an intuitive order (1 =Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, and 5= Strongly Agree), the use of an ordered modeling approach was most appropriate [20]. The observed ordinal variable (y_i) was defined by an unobservable variable (z_i) and estimable thresholds (α), and was coded as:

$$
\begin{aligned}
y_i &= 1 \ if \quad & z_i &\le \alpha_1 \\
y_i &= 2 \ if \quad \alpha_1 < & z_i &\le \alpha_2 \\
y_i &= 3 \ if \quad \alpha_2 < & z_i &\le \alpha_3 \\
y_i &= 4 \ if \quad \alpha_3 < & z_i &\le \alpha_4 \\
y_i &= 5 \ if \quad & z_i &> \alpha_4
\end{aligned}
$$

The resulting regression model had the traditional structure,

$$z_i = \beta X_i + \varepsilon_i$$

where β was a vector of the coefficients, X_i were the independent variables and ε_i was the error term. The probability of an individual having a comfort level equal to j was given by:

$$P(y_i = \text{j}) = \text{F}(\alpha_j - \beta X_i) - \text{F}(\alpha_{j-1} - \beta X_i) \;\; j = 1, 2, 3, 4, 5,$$

where α_0 = -∞ and α_5 = +∞.

This model follows the assumption of parallel lines for ordinal logistic regression, which was validated through the results of the Brant Test [21]. Model fit was evaluated and reported by McFadden's pseudo-R2, log-likelihood, and AIC using Stata [22]. The McFadden's pseudo-R2 formulation was one minus the ratio of the model log-likelihood and intercept-only log-likelihood. Additionally, the marginal effects were computed for model interpretation as they indicate the effect on the outcome category probability resulting from a one-unit change in an independent variable.

Finally, to predict the change in comfort due to the pandemic, regression models were developed for the change in comfort using shared mobility by calculating the difference in comfort between time periods. No change in comfort was represented with a "0", a negative change in comfort ranges from "-1" to "-4", and a positive change in comfort resulting from the pandemic ranged from "1" to "4". Depending on a respondent's starting level of comfort, a truncated number of options were available (e.g. if a respondent first reported "strongly disagree" to feeling comfortable using transit before the pandemic, the only potential changes were [0, 1, 2, 3, 4]). To account for this truncation bias, the starting level of comfort was included as an explanatory variable. Although the dependent variables of change in comfort were ordinal Likert-type variables, linear regression was used to understand the general trends of the data and to explain the difference between transportation modes and periods. Treating a Likert-type ordinal dependent variable as continuous in a linear regression model is considered reasonable when there are four or more ordinal response levels, as seen in this analysis where there were nine potential ordinal response levels [23-24]. An R^2 value was evaluated to show the amount of variance of the outcome that was explained by the predictors, defined as the ratio of the model sum of squares to the total sum of squares. This was adjusted by the number of cases and number of variables to show a more honest association as Adjusted-R2.

4.3. Results and Discussion

4.3.1. Comfort with Shared Mode Use Before COVID-19

Ordinal logistic regression models for the level of comfort in shared mobility before the pandemic, as presented in Table 4-12, indicated a general comfort with shared mobility before COVID-19. The estimated coefficient's significance and value can be interpreted that for each one-unit increase in a continuous explanatory variable, there will be an expected change in the log odds of being in a higher level of level of comfort, given all other variables in the model are held constant; thus a positive coefficient indicates that as the value of the explanatory variable increases, the likelihood of a higher ranking increases. The average marginal effects, reported in Table 4-13, are computed by averaging the marginal effect at each of the sample values of the explanatory variables and can be interpreted as the average effect on the outcome category probability resulting from a one-unit change in an independent variable [25]. The extrovert attitudinal factor, active user and the occasional user indicator were significant and positive across all models. The significance of these positive coefficients suggests that for each mode, if a person previously used the mode “1-3 times a month” or “less than once a month”, or if a person displayed outgoing and extrovert attitudes, they would have tended to be more comfortable using the mode. These results support the hypothesis that interest in shared mobility can be associated with the expression of extraversion, openness, and agreeableness personality traits [26]. The impact of prior experience on comfort supports the school of thought that undertaking unfamiliar travel had the potential to make services easier and more comfortable for them to use by reducing the psychological barriers of uncertainty [27].

In addition to usage of the mode being modeled, a multimodal indicator was significant across shared ride-hailing and transit in predicting comfort. The multimodal indicator was a binomial variable; if an individual used a ride-hail, shared ride-hail, transit, bicycle, shared bicycle, or shared e-scooter at least once a week before the pandemic, they were considered multimodal. This variable was modified for each mode to avoid multicollinearity issues in the model; for example, the transit multimodal variable was 1 if the individual used ride-hail, shared ride-hail, bicycle, shared bicycle, or shared e-scooter at least once a week in the pre-pandemic period. The significance of the multimodal variable was reflective of the interconnected relationship between multimodality and shared mobility [28]. In the private ride-hailing model before the pandemic, active and occasional private ride-hailing users, as well as multimodally inclined respondents, were found to have a higher probability of strongly agreeing that they would feel comfortable using private ride-hailing. The average marginal effects on strongly agreeing were equal to 0.353 and 0.368, for occasional and active users, respectively, indicating that these users had a higher probability of strongly agreeing that they felt comfortable using private ride-hailing before the pandemic. The coefficients for males and respondents with a household income lower than $50K were found to be negative and significant in the private ride-hailing before the pandemic model. On average, males had a 0.066 lower probability to strongly agree, and lower income respondents had a 0.102 lower probability to strongly agree that they felt comfortable using private ride-hailing. The “Follow Safety Measures” and ‘Extrovert” attitude factors were positive and significant in the private ride-hailing model. This indicates that that people who adhere to suggested rules and were comfortable around others tend to be more comfortable than others with the sharing experience.

The “Extrovert” and “Follow Safety Measures” factors were also positive and significant in the model of public transit comfort before the pandemic. Unlike the private ride-hailing and shared ride-hailing models, no socio-demographic variables were found to be significant in the transit model. Prior usage variables were significant in predicting the level of comfort using transit; active transit users had on average a 0.334 higher probability to strongly agree, occasional transit users had on average a 0.291 higher probability to strongly agree, and multimodal transportation users a 0.103 higher probability to strongly agree that they felt comfortable using transit before the pandemic.

This trend of prior usage with the mode impacting comfort continued in the shared ride-hailing model as the average marginal effect on strongly agreeing for an active user was 0.204, which indicates that prior usage results in a higher probability to strongly agree that they felt comfortable using shared ride-hailing. Unlike the transit and private ride-hailing models which found similar influence levels from active and occasional users, occasional users in the shared ride-hailing model had only a 0.005 higher probability than others of strongly agreeing that they would feel comfortable using shared ride-hailing before the pandemic. This finding indicated that attitudes towards shared ride-hailing were complex and should be examined further. Age and income indicator variables were negative and significant in the shared ride-hailing model. Respondents from the "Boomer" generation (56-74 yrs. old) and respondents with a household income more than $100K were found to be less comfortable using shared ride-hailing services. This finding was consistent with previous studies [29].

TABLE 4-14: ORDINAL LOGIT MODEL OF COMFORT BEFORE THE COVID-19 PANDEMIC FOR SHARED MODES

Ordinal Logistic Model of Comfort Before the COVID-19 Pandemic						
Variable	Private Ride-Hailing		Shared Ride-Hailing		Public Transit	
	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
Attitude Factors						
Follow Safety Measures	0.307	***			0.372	***
Extrovert	0.241	**	0.493	***	0.175	*
Trust Precautions			0.279	***		
Socio-Demographics						
Male Indicator	-0.334	*				
Age Indicator (Boomer)			-0.495	**		
Lower Income Indicator (<$50K)	-0.513	**				
Higher Income Indicator (>$100K)			-0.466	***		
Prior Usage Indicators						
Occasional User	1.776	***	0.747	***	1.391	***
Active User	1.865	***	1.152	***	1.593	***
Multimodal User	0.388	*	0.279	*	0.489	**
Thresholds						
α_1	-2.806		-2.437		-2.200	
α_2	-1.965		-0.785		-0.913	
α_3	-0.915		-0.046		-0.080	
α_4	1.018		1.424		1.644	
# of Responses	787		787		787	
Intercept-only log likelihood	-779.447		-1188.703		-982.223	
Final log likelihood	-703.684		-1114.171		-896.770	
McFadden Pseudo R^2	0.0972		0.0627		0.0870	
McFadden Adjusted Pseudo R^2	0.0879		0.0518		0.0788	

*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$

TABLE 4-15: AVERAGE MARGINAL EFFECTS OF THE ORDINAL LOGIT MODEL ESTIMATION OF COMFORT BEFORE THE COVID-19 FOR SHARED MODES

Marginal Effects: **Private Ride-Hailing** Before the COVID-19 Pandemic					
	Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
Follow Safety Factor	-0.006	-0.006	-0.013	-0.036	0.061
Extrovert Factor	-0.005	-0.005	-0.010	-0.028	0.048
Male Indicator	0.007	0.007	0.014	0.039	-0.066
Lower Income Indicator	0.010	0.010	0.022	0.060	-0.102
Occasional User Indicator	-0.036	-0.035	-0.076	-0.206	0.353
Active User Indicator	-0.037	-0.037	-0.079	-0.215	0.368
Multimodal Indicator	-0.008	-0.008	-0.017	-0.045	0.077
Marginal Effects: **Shared Ride-Hailing** Before the COVID-19 Pandemic					
	Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
Extrovert Factor	-0.033	-0.054	-0.017	0.017	0.087
Trust Precautions Factor	-0.189	-0.030	-0.010	0.010	0.049
Age Indicator (Boomer)	0.032	0.051	0.016	-0.016	-0.083
High Income Indicator	0.029	0.047	0.015	-0.015	-0.076
Occasional User Indicator	-0.019	-0.030	-0.010	0.010	0.050
Active User Indicator	-0.078	-0.125	-0.040	0.039	0.204
Multimodal Indicator	-0.050	-0.081	-0.026	0.025	0.132
Marginal Effects: **Transit** Before the COVID-19 Pandemic					
	Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
Follow Safety Factor	-0.012	-0.020	-0.019	-0.027	0.078
Extrovert Factor	-0.006	-0.009	-0.009	-0.013	0.037
Active User Indicator	-0.053	-0.086	-0.081	-0.114	0.334
Occasional User Indicator	-0.046	-0.075	-0.071	-0.099	0.291
Multimodal Indicator	-0.016	-0.026	-0.025	-0.035	0.103

4.3.2. Comfort of Shared Mode Use During COVID-19

Ordinal logistic regression models for the level of comfort using shared mobility during the pandemic assuming the October 2020 Atlanta metro area COVID-19 risk, as presented in Table 4-14, indicated that the attitudes related to the "Follow Safety Measures" factor negatively influenced level of comfort across all modes and "Trust Precautions" positively influenced level of comfort across all modes. As the factor related to the importance of wearing masks and air circulation increased for individuals, the level of comfort using all shared modes decreased. As the factor that measures trust in the sanitization measures of shared mobility increased for individuals, the level of comfort using all shared modes increased. The variable related to awareness of virus spread, "Germophobe" attitude factor, was negative and significant in the private ride-hailing and transit models. As the spread of the virus becomes more important for individuals, their level of comfort using private ride-hailing and transit decreases. This variable was not found to be significant in the shared ride-hailing model. This difference between modes may have been due to the suspension of shared ride-hailing services and the resulting lack of understanding of comfort levels using this mode. Unlike the level of comfort before the pandemic models, the extrovert factor was not included in this model as it was not statistically significant. During the pandemic, even being an extrovert did not influence one's level of comfort using shared mobility.

TABLE 4-16: ORDINAL LOGIT MODEL OF COMFORT DURING THE PANDEMIC (OCTOBER 2020) FOR SHARED MODES

Ordinal Logistic Model of Level of Comfort During the COVID-19 Pandemic						
Variable	Private Ride-Hailing		Shared Ride-Hailing		Public Transit	
	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
Attitude Factors						
Follow Safety Measures	-0.390	***	-0.691	***	-0.219	**
Trust Precautions	0.993	***	1.059	***	0.688	***
Germaphobe	-0.155	*			-0.266	***
Prior Usage Indicator						
Non-User	-0.949	***	-0.424	**	-0.867	***
Thresholds						
α_1	-1.833		-0.175		-0.930	
α_2	-0.328		1.581		0.509	
α_3	0.381		2.513		1.271	
α_4	1.927		3.770		2.825	
# of Responses	787		787		787	
Intercept-only log likelihood	-1243.485		-968.226		-1144.863	
Final log likelihood	-1126.946		-830.537		-1091.617	
McFadden Pseudo R^2	0.0937		0.1422		0.0630	
McFadden Adjusted Pseudo R^2	0.0844		0.1345		0.0534	

*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$

TABLE 4-17: AVERAGE MARGINAL EFFECTS OF THE ORDINAL LOGIT MODEL ESTIMATION OF COMFORT DURING THE COVID-19 FOR SHARED MODES

Marginal Effects: **Private Ride-Hailing** During the COVID-19 Pandemic					
	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Follow Safety Factor	0.053	0.024	-0.002	-0.031	-0.044
Trust Precautions Factor	-0.135	-0.062	0.006	0.078	0.113
Germaphobe Factor	0.0211	0.009	-0.001	-0.122	-0.018
Non-User Indicator	0.129	0.059	-0.006	-0.075	-0.108

TABLE 4-18: CONTINUED

Marginal Effects: **Shared Ride-Hailing** During the COVID-19 Pandemic	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Follow Safety Factor	0.127	-0.037	-0.033	-0.033	-0.023
Trust Precautions Factor	-0.194	0.057	0.508	0.508	0.035
Non-User Indicator	0.078	-0.023	-0.020	-0.020	-0.014

Marginal Effects: **Transit** During the COVID-19 Pandemic	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Follow Safety Factor	0.043	0.000	-0.010	-0.021	-0.012
Trust Precautions Factor	-0.136	-0.000	0.032	0.066	0.038
Germaphobe Factor	0.053	0.000	-0.013	-0.026	-0.015
Non-User Indicator	0.172	0.000	-0.041	-0.084	-0.048

Prior usage impacted level of comfort across all modes during the pandemic. A dummy variable for respondents who had never used the mode (non-users) was significant and negative in all shared modes during the pandemic. A transit non-user had, on average, a 0.172 higher probability of strongly disagreeing that they felt comfortable using transit during the pandemic. A private ride-hailing non-user had, on average, a 0.129 higher probability of strongly disagreeing that they felt comfortable using private ride-hailing during the pandemic. The smallest non-user impact on comfort during the pandemic was estimated in shared ride-hailing; non-users had, on average, only a 0.078 higher probability of strongly disagreeing that they felt comfortable using that mode during the pandemic, as seen in Table 4-15.

4.3.3. Comfort of Shared Modes Post-COVID-19

Ordinal logistic regression models for the level of comfort in shared mobility in the future when a vaccine became available was predicted, as presented in Table 4-16. Similar to the before COVID models, the future models included the extroversion attitude, which increased level of comfort across all modes. The variables related to awareness of virus spread, germophobe attitude factor, were negative and significant in the transit model. More germ-conscious individuals were less comfortable using transit in the future than other users. The factor related to following safety measures was only significant and positive in the transit model after the pandemic.

Sociodemographic characteristics in the models reveals the non-white variable negatively impacts the level of comfort with all shared modes in the future. As seen in Table 4-17, a respondent that identifies as a race other than White / Caucasian had on average a 0.138, 0.161, and 0.118 lower probability of strongly agreeing that they would feel comfortable using ride-hailing, shared ride-hailing, and transit, respectively, after the pandemic. Income variables were significant in the private ride-hailing and shared ride-hailing models. The marginal effects indicated that respondents with an annual household income of $50K or less had a 0.097 lower probability of strongly agreeing that they will feel comfortable using private ride-hailing in the future and respondents with a household income of $100K or more had a 0.051 lower probability of strongly agreeing that they will feel comfortable using shared ride-hailing in the future. The male indicator variable was positive and significant in the shared ride-hailing and transit models. As females were typically more inclined to use shared ride-hailing and transit, this result may be influenced by men's willingness to take risks and ride in shared modes post-pandemic; other studies have found that being male was uniformly associated with lower risk perceptions [30]. Indicator variables for generation groups of "Boomer" and "Gen Z" were negative and significant in the shared ride-hailing and transit models respectively. Gen Z respondents (aged 18-24) were less likely to agree or strongly agree that they would feel comfortable using transit in the future when a vaccine became available. Respondents in the "Boomer" generation (56-74 years old) were less likely to agree or strongly agree that they would feel comfortable using shared ride-hailing in the future.

TABLE 4-19: ORDINAL LOGIT MODEL OF COMFORT POST-PANDEMIC (WITH A VACCINE) FOR SHARED MODES

Ordinal Logistic Model of Level of Comfort Post-COVID-19						
Variable	Private Ride-Hailing		Shared Ride-Hailing		Public Transit	
	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
Attitude Factors						
Follow Safety Measures					0.222	**
Extrovert	0.121	*	0.393	***	0.135	*
Trust Precautions	0.507	***	0.563	***	0.384	***
Germaphobe					-0.199	**
Socio-Demographic Factors						
Male Indicator			0.493	***	0.323	*
Age Indicator (Boomer)			-0.065	***		
Age Indicator (Gen Z)					-0.724	**
Racial Indicator (Non-White)	-0.718	***	-0.615	***	-0.759	***
Lower Income Indicator	-0.505	**				
Higher Income Indicator			-0.513	***		
Prior Usage Indicators						
Occasional User	1.259	***	0.431	**	1.093	***
Active User	1.643	***	0.663	*	1.014	***
Multimodal User			0.305	*	0.314	*
Thresholds						
α_1	-2.862		-2.255		-2.166	
α_2	-1.750		-1.859		-0.626	
α_3	-0.314		-0.088		0.590	
α_4	1.702		2.371		2.400	
# of Responses	787		787		787	
Intercept-only log likelihood	-1038.623		-1219.6658		-1172.287	
Final log likelihood	-963.028		-1122.702		-1072.056	
McFadden Pseudo R^2	0.0728		0.0795		0.0855	
McFadden Adjusted Pseudo R^2	0.0534		0.0640		0.0689	

*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$

TABLE 4-20: AVERAGE MARGINAL EFFECTS OF THE ORDINAL LOGIT MODEL ESTIMATION OF COMFORT AFTER THE COVID-19 PANDEMIC FOR SHARED MODES

Marginal Effects: **Private Ride-Hailing** Post-COVID-19					
	Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
Extrovert Factor	-0.004	-0.005	-0.011	-0.003	0.023
Trust Precautions Factor	-0.017	-0.023	-0.047	-0.011	0.097
Lower Income Indicator	0.017	0.023	0.047	0.011	-0.097
Race Indicator (Non-White)	0.024	0.032	0.067	0.015	-0.138
Occasional User Indicator	-0.042	-0.057	-0.117	-0.027	0.242
Active User Indicator	-0.054	-0.074	-0.152	-0.035	0.316
Marginal Effects: **Shared Ride-Hailing** Post-COVID-19					
	Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
Extrovert Factor	-0.037	-0.042	0.005	0.052	0.053
Trust Precautions Indicator	-0.052	-0.060	0.001	0.055	0.056
Male Indicator	-0.046	-0.052	0.001	0.048	0.049
Higher Income Indicator	0.048	0.054	-0.001	-0.050	-0.051
Race Indicator (Non-White)	0.057	0.065	-0.002	-0.060	-0.061
Age Indicator (Boomer)	0.060	0.068	-0.002	-0.063	-0.064
Occasional User Indicator	-0.040	-0.046	-0.017	0.005	0.069
Active User Indicator	-0.068	-0.070	0.002	0.065	0.065
Multimodal Indicator	-0.02	-0.032	0.001	0.030	0.030
Marginal Effects: **Transit** Post-COVID-19					
	Strongly Disagree	*Disagree*	*Neither Agree nor Disagree*	*Agree*	*Strongly Agree*
Safety Measures Factor	-0.012	-0.0188	-0.014	0.010	0.035
Extrovert Factor	-0.007	-0.011	-0.008	0.006	0.021
Trust Precautions	-0.021	-0.033	-0.024	0.017	0.060
Germaphobe Factor	0.011	0.017	0.012	-0.009	-0.031
Male Indicator	-0.018	-0.027	-0.020	0.015	0.050
Race Indicator (Non-White)	0.041	0.064	0.047	-0.034	-0.118
Age Indicator (Gen Z)	0.040	0.061	0.045	-0.032	-0.113
Occasional User Indicator	-0.060	-0.093	-0.067	0.049	0.170
Active User Indicator	-0.055	-0.0859	-0.062	0.046	0.158
Multimodal Indicator	-0.017	-0.027	-0.019	0.014	0.049

4.3.4. Difference in Level of Comfort Models for Shared Modes

To understand changes in reported comfort due to the pandemic, three groups of linear regression models estimated the difference in level of comfort for private ride-hailing, shared ride-hailing, and transit between three periods (before COVID-19, October 2020, and the future when a vaccine became available). The difference in comfort level was defined by subtracting respondents' reported Likert-style level of comfort (i.e. 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree) between periods. This resulted in scores ranging from -4 (i.e. level of comfort changing from "Strongly Agree" to "Strongly Disagree") to +4 (i.e. level of comfort changing from "Strongly Disagree" to "Strongly Agree"). Depending on a respondent's starting level of comfort, only a truncated number of options were available for the difference in level of comfort (e.g. if a respondent first "strongly disagreed" with feeling comfortable using transit before the pandemic, the only potential changes were [0, 1, 2, 3, 4]). To account for this truncation bias, the starting level of comfort was included as an explanatory variable, "Previously Reported Comfort Attitude".

4.3.4.1. Difference in Level of Comfort Between October 2020 and Pre-COVID-19

Models of the difference in reported level of comfort October 2020 and pre-COVID-19 reflected the overall decrease in comfort with using shared mobility due to the pandemic, as seen in Table 4-18; all models estimated negative constants for all previously reported comfort attitudes and negative coefficients for the "strongly agree" and "agree" previously reported comfort attitudes. This dramatic shift in comfort with using shared ride-hailing during the pandemic may have been impacted by outside perspectives as shared ride-hailing services were suspended during the pandemic due to safety concerns.

TABLE 4-21: LINEAR REGRESSION MODELS OF DIFFERENCE IN LEVEL OF COMFORT BETWEEN OCTOBER 2020 AND PRE-COVID-19 FOR SHARED MODES

Difference in Level of Comfort between October 2020 and Pre-COVID-19

Variable	Private Ride-Hailing			Shared Ride-Hailing			Transit		
	Coeff.	Std. Err.	Sig.	Coeff.	Std. Err.	P	Coeff.	Std. Err.	P
Attitude Factors									
Follow Safety Measures	-0.286	(0.035)	***	-0.296	(0.352)	***	-0.189	(0.041)	***
Trust Precautions	0.593	(0.036)	***	0.406	(0.035)	***	0.402	(0.041)	***
Socio-Demographics									
Higher Income Indicator (> $50K)							-0.190	0.097	*
Previously Reported Comfort Attitude									
Strongly Disagree	0.372	(0.104)		1.255	(0.102)	***	0.833		**
Disagree	0.164	(0.096)		0.624	(0.095)	***	0.406		*
Agree	-1.080	(0.103)	***	-0.961	(0.102)	***	-1.096		***
Strongly Agree	-1.891	(0.112)	***	-2.045	(0.109)	***	-1.677		***
Constant	-0.103	(0.083)		-1.045	(0.081)	***	-0.806		***
# of Responses		787			787			787	
Adjusted R^2		0.399			0.632			0.403	

**P* < 0.05, ***P* < 0.01, ****P* < 0.001

The linear models indicated that the attitudinal factors related to safety measures and trusting shared mobility precautions were significant to the change in level of comfort across all shared mobility modes between pre-COVID and October 2020. The factor for following safety measures was negative across all modes which meant that if an individual indicated the importance of following safety measures like wearing masks, their level of comfort using shared mobility during the pandemic was likely to decrease when compared to their level of comfort before. The factor related to trusting the precautions taken by shared mobility was significant and positive in models across all shared mobility modes; that means that if an individual indicated they trust the sanitization and social distancing measures of ride-hailing and transit, their level of comfort with using shared mobility during the pandemic was not as likely to decrease when compared to their level of comfort with using shared mobility before the pandemic. Sociodemographic characteristics in the models revealed only a higher income indicator (i.e. household income of $50K or more) was significant and negative in transit change in comfort models. This indicated that levels of comfort using transit were more negatively impacted by the pandemic for higher income individuals. Income was not a significant factor in shared ride-hailing and private ride-hailing models. Other demographic variables including age, race, and gender were not significant in the models.

4.3.4.2. Difference in Level of Comfort Between the Future (with a vaccine) and October 2020

Linear regression models for the difference in level of comfort in shared mobility between the future (when a vaccine became available) and October 2020, presented in Table 4-19, indicated that respondents reported a slight increase in comfort across all modes when a vaccine was available compared to October 2020 during the pandemic; the previous reported comfort attitude constants were positive which meant that there was a positive average impact on change-in-comfort of all unobserved variables. The attitude related to following safety measures positively influences change in level of comfort across all modes; if an individual indicated the importance of following safety measures like wearing masks, their level of comfort using shared mobility after the pandemic will likely increase when compared to their level of comfort during the pandemic.

Table 4-22: Linear Regression Models of Difference in Level of Comfort Between the Future (when a vaccine is available) and October 2020 for Shared Modes

Difference in level of comfort between October 2020 and the "future when a vaccine is available"									
Variable	Private Ride-Hailing			Shared Ride-Hailing			Transit		
	Coeff.	Std. Err.	P	Coeff.	Std. Err.	P	Coeff.	Std. Err.	P
Attitude Factors									
Follow Safety Measures	0.296	(0.039)	***	0.239	(0.037)	***	0.247	(0.042)	***
Trust Precautions	-0.364	(0.046)	***	-0.189	(0.045)	***	-0.209	(0.046)	***
Socio-Demographics									
Non-White Indicator	-0.527	(0.091)	***	-0.378	(0.087)	***	-0.414	(0.104)	*
Male Indicator				0.181	(0.082)	*	0.208	(0.095)	**
Millennial (25-40 yrs. old)				0.421	(0.101)	***	0.248	(0.085)	**
Gen X (41-55 yrs. old)				0.284	(0.097)	**			
Higher Income Indicator (> $50K)							0.342	(0.090)	***
Previous Reported Comfort Attitude									
Strongly Disagree	0.936	(0.366)	*	-0.427	(0.185)	*	0.265	(0.279)	
Disagree	0.114	(0.250)		-0.380	(0.113)	**	-0.084	(0.187)	
Agree	0.399	(0.179)	*	0.284	(0.113)	*	0.472	(0.134)	***
Strongly Agree	0.710	(0.170)	***	0.768	(0.121)	***	0.619	(0.132)	***
Constant	0.633	(0.166)	***	0.768	(0.112)	***	0.849	(0.128)	***
# of Responses		787			787			787	
Adjusted R^2		0.217			0.206			0.174	

*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$

As for sociodemographic characteristics, we found that a higher income resulted in an increase in comfort for transit. This may reflect the return to comfort for transit "choice riders" with a higher income in a post-pandemic world. Unlike the model of the changes in comfort level from before to during the pandemic, additional demographic variables including race, gender, and age were significant in explaining the change from October 2020 to the post-pandemic period. In the model, an indicator variable representing people who did not identify as white was significant and negative in all shared modes which means that the white population would be expected to have a larger increase (or smaller decrease) in comfort levels with shared mobility after a vaccine was available than non-whites, all else equal. Variables for generational age groups of Millennials (25-40 yrs. old) were positive for the difference in comfort for shared ride-hailing and transit which reflected a return to feeling more comfortable using shared ride-hailing and transit post-pandemic for the younger population compared to non-Millennials. This may be due to the risk for severe illness with COVID-19 which increased with age, with older adults at highest risk. A gender variable in the shared ride-hailing and transit models indicated that post-COVID, the comfort levels for these modes will increase more (or decrease less) for males than for females, all else equal, which was consistent with the generalization that females were more risk-averse.

4.3.4.3. Difference in Level of Comfort Between the Future (with a Vaccine) and Pre-Pandemic for Shared Modes

A model comparing the difference in comfort between post-pandemic and pre-pandemic periods was developed to examine the longer lasting impacts of COVID-19, as displayed in Table 4-20. Across all modes, the trusting precautions factor was predicted as positive and significant in difference in comfort from post- to pre-pandemic. This indicates that that trusting the efforts taken by shared mobility (e.g. sanitize and distance passengers) positively impacted the longer-term difference in comfort. The difference of level of comfort for respondents who reported that they never used shared mobility before the pandemic will decrease more (increase less) than active and occasional users. The pandemic negatively impacted non-users' longer-term perception of comfort on shared mobility. Similar to the prior models in Section 4.4.4.2 (the difference in level of comfort between the future (with a vaccine) and October 2020), the models of the difference in level of comfort between the future and pre-pandemic, as seen in Table 4-20, include a significant and positive millennial indicator in shared ride-hailing, significant and positive male indicators across shared modes, and significant and negative non-white indicators across all shared modes.

TABLE 4-23: LINEAR REGRESSION MODELS OF DIFFERENCE IN LEVEL OF COMFORT BETWEEN THE FUTURE (WITH A VACCINE) AND BEFORE THE PANDEMIC FOR SHARED MODES

Difference in level of comfort between before COVID-19 and the future "when a vaccine is available"

Variable	Private Ride-Hailing			Shared Ride-Hailing			Transit		
	Coeff.	Std. Err.	P	Coeff.	Std. Err.	P	Coeff.	Std. Err.	P
Attitude Factor									
Trust Precautions	0.232	(0.038)	***	0.229	(0.040)	***	0.204	(0.036)	***
Socio-Demographics									
Non-White Indicator	-0.432	(0.076)	***	-0.376	(0.081)	***	-0.524	(0.080)	***
Male Indicator	0.132	(0.063)	*	0.284	(0.073)	***	0.247	(0.069)	***
Millennial (25-40 yrs. old)				0.169	(0.075)	*			
Prior Modal Usage									
Non-User	-0.412	(0.116)	***	-0.239	(0.083)	**	-0.452	(0.100)	***
Previous Reported Comfort Attitude									
Strongly Disagree	1.333	(0.373)	***	0.900	(0.160)	***	1.148	(0.295)	***
Disagree	0.433	(0.275)		0.346	(0.098)	**	0.383	(0.159)	*
Agree	-0.783	(0.130)	***	-0.708	(0.099)	***	-0.760	(0.127)	***
Strongly Agree	-0.131	(0.130)	***	-1.410	(0.115)	***	-1.219	(0.129)	***
Constant	0.600	(0.134)	***	0.083	(0.104)		0.326	(0.129)	***
# of Responses		787			787			787	
Adjusted R^2		0.309			0.377			0.318	

*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$

4.4. Conclusions and further research

This study provides important insight into the comfort with and usage of shared modes before the pandemic, during a re-opening phase of the pandemic, and in the predicted future when a vaccine was available. Data collected from the Atlanta area in October 2020 does not represent the general population as it oversampled high-income respondents. Additionally, this study under-sampled active users of shared mobility. Despite these limitations, trends seen in regression models and data analysis were important to predict the long-term impact of COVID-19 on our willingness to use shared mobility. Due to social distancing and stay-at-home orders during the pandemic, the usage of shared mobility transportation modes significantly decreased when compared to usage before the pandemic. Potential virus exposure from other riders contributed to a lower level of comfort for shared modes throughout the pandemic despite the reopening of the economy. In response to this discomfort, shared modes implemented many precautionary measures including suspending shared ride-hailing, requiring all passengers and drivers to wear masks, and encouraging social distancing and air circulation. These measures were generally viewed as positive and a portion of the population that trusts these precautions did not indicate a change in comfort during the pandemic for shared modes.

In the future, comfort levels associated with using shared mobility were expected to increase but not completely return to previous levels. The change in levels of comfort post-pandemic varied among socio-demographic variables like race, income, and age. Post-vaccine as the world returns to a “new normal”, this research provides essential insights for planners and policymakers to better prepare for the post-pandemic era.

As this research utilized self-reported preferences, a gap between the reported and real preferences may exist due to limitations; respondents may not be capable of predicting their behavior in a future hypothetical scenario or respondents may not actually remember and report their past behavior. To build on this work, further research should collect and analyze the changes to comfort and actual usage over multiple periods and for trip individual purposes. As more survey data becomes available, this analysis should be extended across cities and compared to develop local and national trends.

5.0. Feeling Positive About a New Normal? The Shifting Perceptions on Shared Mobility throughout the Covid-19 Pandemic

5.1. Introduction

The COVID-19 pandemic was a major disruption from March 2020 through at least mid-July 2022, as the threat was still declared a US national emergency at the time of writing this report. Dramatic changes to travel behavior were reported at the start of the pandemic but as new knowledge was obtained about how the virus spreads, vaccines were widely distributed, and individuals developed skills to manage the ongoing threat over two years, attitudes and behaviors have begun to shift back toward pre-pandemic levels. At the start of the pandemic, the use of public transit and other shared modes declined as modal preferences shifted due to safety, comfort, cleanliness, and infection concerns [1]. In an attempt to lower the risk of potential virus exposure, ride-hailing, and public transit agencies initiated several safety precautions (i.e. requiring masks, limiting the number of passengers, and providing sanitation resources). Although these measures alleviated some of the high transmission risks, the impact of reducing *perceived* risk was still limited by anxiety about shared spaces [2]. The perceived risk of using shared modes varied among individuals (e.g. perceived risk was higher in females and older populations) and was expected to be the main barrier to ridership recovery until COVID was no longer a public threat [3-4].

The transmission risk of the virus continued to remain a public threat for a longer period than initially expected. Many health experts suggested that COVID-19 will result in a “new normal” scenario where the public lives with an endemic status where COVID is consistently present but limited to particular regions, instead of a pandemic [5]. “Next normal” scenarios mean the COVID-19 virus will result in long-term impacts and be considered a constant threat that needs to be managed. Looking to the “post”-COVID future, the public may never return to their pre-COVID behaviors and attitudes. Although intentions toward ride-hailing, ride-sharing, and transit were expected to increase as the severity of the pandemic decreases [4, 6-7] the rate and final magnitude of this increase were unknown. To understand the intentions of shared mobility use throughout the pandemic and in a “new normal”, this study examined changes in the reported level of comfort of using solo ride-hailing, shared ride-hailing, and transit over time. Additionally, this study compared the level of comfort in different shared scenarios with and without masks to examine situational aspects of shared spaces.

Recent academic literature has captured cross-sectional data to estimate and forecast the impacts of the pandemic on transportation attitudes [1, 7-8]. These studies provided excellent initial insight into shared mobility attitudes at specific times; a survey by Kopsidas et al (2021) in May 2020 found that older age groups expected to refrain from using public transit for a long period after the pandemic [8]. A single transportation preference survey can retrospectively and/or prospectively collect multiple time frames by asking respondents to remember past attitudes and/or predict how they might feel in future scenarios [9]. A multi-wave panel survey was another option to understand temporal impacts and has added richness to understanding a more granular change in individuals. Panel data analysis during COVID-19 had been conducted at the start of the pandemic [10-11] but there is a current gap in the literature on a longitudinal panel throughout the many stages of the long-lasting pandemic. This study starts to address this gap by analyzing a two-wave panel survey completed in October 2020 and October 2021 and examining recalled and predicted attitudes over an almost two-year period. This study was one of the first to examine transportation attitudes and behaviors in the "new normal" period.

5.2. Data and Methodology

5.2.1. Data Collection

The two-wave online survey, hosted on the Qualtrics platform, was distributed in October 2020 and October 2021 to adults in the metro Atlanta, GA area. During each wave of the survey, respondents were asked to report their level of comfort using shared mobility in specified "past", "present", and "future" periods. In the Wave 1 survey, respondents recalled their attitudes before the pandemic (~8 months prior), estimated their attitudes in the current period (October 2020), and predicted their attitudes in the future when a vaccine would be available. The Wave 1 survey was distributed after the initial COVID infection wave in Atlanta, Georgia, as seen in Figure 5-1. The Wave 2 survey was distributed after the COVID Delta variant infection wave in Atlanta. The two "current" periods occurred when COVID cases were low. In the Wave 2 survey, respondents recalled their attitudes during the summer of 2021 when COVID cases were high (~3 months prior), estimated their attitudes in the current period (October 2021), and predicted their attitudes a year in the future (October 2022).

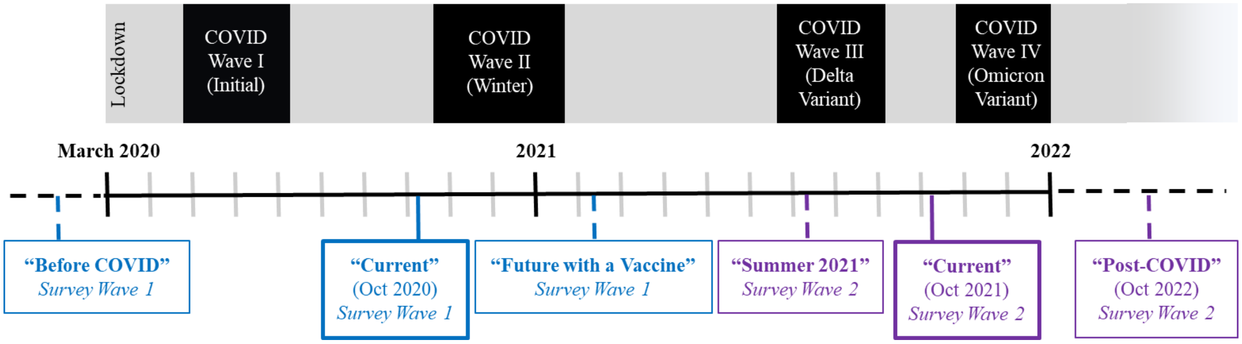


FIGURE 5-1: TIMELINE OF COVID-19 AND SURVEY DISTRIBUTION

The Wave 2 online survey was sent out on October 7, 2021 to an email address distribution list comprising 417 Wave 1 survey participants that indicated they would be interested in completing future surveys. These respondents were originally recruited into Wave 1 of the study by email recontact, community outreach, and Facebook ads. The full Wave 1 sample was originally 787 individuals (almost double the size of the Wave 2 panel distribution list) but due to recruitment method limitations on collecting personal identifiable information, only a portion of the Wave 1 sample was invited to join the panel. A detailed description of the sampling methodology can be found in Chapter 3 of this report.

The survey content distributed in the Wave 2 survey was very similar to that of Wave 1, with only minor modifications including updating the time frame of questions and adding/removing statements to reflect current pandemic conditions. There was no monetary incentive for participants to complete either wave of the survey. To increase response rates for the longitudinal panel, unfinished respondents were sent three reminder emails, on Tuesday, October 12th, Monday, October 18th, and Friday, October 22nd, 2021. The Wave 1 survey collected responses between October 7th and 30th, 2021.

5.2.2. Data Description

Of the 417 surveys distributed to Wave 1 respondents, 191 participants started the Wave 2 survey, as displayed in Table 5-1 (and Figure 3-2 in Chapter 3). Most Wave 2 survey respondents who attempted the survey completed it as there were only 15 incomplete surveys (resulting in a completion rate of 92.1%). The response rate of the survey, calculated by dividing the number of people who completed the survey by the number of people who made up the total sample group, was high at 42.2%. Collected data was cleaned by removing respondents with incomplete surveys, incoherent fill-in-the-blanks, flatlining on the matrix table, failing the shared ride-hailing usage attention trap question, and providing a zip code outside of the Atlanta metro area. No completed survey response failed the shared ride-hail usage attention question, flatlined on the matrix table, or entered incoherent text for the fill-in-the-blank responses. Only four surveys contained zip codes outside of the Atlanta area. The Wave 2 data collection process resulted in 172 clean and completed surveys. Data was further cleaned by connecting Wave 1 responses and removing 10 cases where the birth year and/or race changed indicating a different survey respondent. The high response rate, high completion rate, and low number of data errors may have suggested that the respondents who agreed to be contacted again after Wave 1 were dedicated and strongly motivated to share their opinions.

TABLE 5-1: WAVE 2 RESPONSES

Panel Recruitment Method	Wave 2 Surveys Distributed	Wave 2 Surveys Started	Wave 2 Surveys Completed	Wave 2 Response Rate %	Clean Surveys	Matching with Wave 1
Email Recontact	216	120	112	51.9%	108	102
Community Outreach	153	51	45	29.4%	45	41
Facebook Ads	48	20	19	39.6%	19	19
Combined Sample	417	191	176	42.2%	172	162

5.2.2.1. Socio-Demographics

The 162 complete and valid surveys resulted in a sample that over-represented female, higher-educated, higher-income, and white populations when compared with the population of the Atlanta metro area, as displayed in Table 5-2. This result mirrors the sampled population from the Wave 1 survey, which over-represented similar groups. Compared to the Wave 1 survey, the panel recruited fewer young respondents, especially in the Gen Z group (18-24 yrs. old), more female respondents, and fewer low-income respondents, as presented in Table 5-3. Wave 2 respondents listed 42 unique home zip codes around the Atlanta metro area; the largest number of respondents were from 30312 (n=33), 30307 (n=22) and 30316 (n=20). Although this does not reflect the general Atlanta-metro population, it does sample the ideal environment for shared mobility, namely urban areas with accessible transit.

TABLE 5-2: DISTRIBUTION OF DEMOGRAPHICS FOR WAVE 2 SURVEY RESPONDENTS

		Responses (n=162)	% of Respondents	Percentage Point Difference between Population* and Sample
Household Income	Less than $25,000	11	6.8%	- 17.0%
	$25,00 - $49,999	17	10.5%	- 7.1%
	$50,00 - $74,999	18	11.1%	- 3.9%
	$75,00 - $99,999	17	10.5%	- 0.4%
	$100,000 - $149,999	43	26.5%	+ 13.9%
	More than $150,000	56	34.6%	+ 14.5%
Gender	Female	102	63.0%	+ 11.7%
	Male	58	35.8%	- 12.9%
	Prefer to Self-Describe	2	1.2%	
Respondent Age	18-34	17	10.5%	- 25.2%
	35-49	63	38.9%	+ 19.0%
	50-64	52	32.1%	+ 16.8%
	65+	30	18.5%	+ 6.9%
*Race / Ethnicity***	White / Caucasian	131	80.9%	+ 41.1%
	Black / African American	23	14.2%	- 33.0%
	Hispanic / Latino	7	4.3%	- 1.7%
	Asian / Pacific Islander	6	3.7%	- 1.1%
	Other	4	1.8%	- 7.0%
Education	Lower than a bachelor's degree	20	12.3%	- 34.3%
	Bachelor's degree	56	34.6%	+ 4.8%
	Graduate or Professional Degree	86	53.1%	+ 29.5%

* From 2020 ACS estimates. "-" indicates the sample has a smaller share than the population
** Respondents were allowed to mark more than one

Respondents were asked to report their prior usage frequency of ride-hailing, shared ride-hailing, and transit to identify types of shared mobility users. Non-users indicated that they "Never" used a mode before the pandemic, occasional users indicated that they used the mode "1-3 times a month" or "less than once a month", and active users indicated that they used the mode at least once a week. Multimodal users indicated the use of a bicycle, shared e-scooter, transit, or ride-hailing at least once a week. Most panel respondents had recent experiences using ride-hailing and transit (as active or occasional users) but not shared ride-hailing before the pandemic.

TABLE 5-3: DISTRIBUTION OF PANEL TRANSPORTATION CHARACTERISTICS

		Responses (n=162)	% of Respondents	Percentage Point Difference from Wave 1
Generation Indicator	Gen Z (18-24 yrs. old)	0	0%	- 6.6%
	Millennial (25-40 yrs. old)	38	23.5%	- 9.2%
	Gen X (41-55 yrs. old)	65	40.1%	+ 0.1%
	Boomer (56-74 yrs. old)	52	32.1%	+ 11.5%
	Silent (75+ yrs. old)	7	4.3%	+ 4%
Income Indicator	Lower than $50K Income	17	10.5%	- 12.3%
	Higher than $100K Income	99	61.1%	+ 10.7%
Prior Ride-Hailing Usage Indicator	Active User	19	11.7%	- 1.9%
	Occasional User	127	78.4%	+ 12.3%
	Non-User	16	9.9%	- 8.6%
Prior Shared Ride-Hailing Usage Indicator	Active User	2	1.2%	- 6.6%
	Occasional User	58	35.8%	- 6.8%
	Non-User	102	63.0%	+ 13.4%
Prior Transit Usage Indicator	Active User	36	22.2%	+ 1.4%
	Occasional User	103	63.6%	+ 6.8%
	Non-User	23	14.2%	- 8.4%
Multimodal User Indicator		67	41.4%	+ 5.7%

"-" indicates less than Wave 1 and "+" indicates more than Wave 1

The disruption of the economy from the pandemic resulted in employment status changes for many people across the globe as employees shifted to working online or were laid off; in this sample the percentage of unemployed respondents increased by 5.6 percentage points (from 2 to 11 respondents) from pre-COVID to Fall 2020, as displayed in Table 5-4. Before the pandemic, 71.6% of the sample worked full-time. In Fall 2020, the percentage of the sample working full-time decreased to 64.2% and slowly recovered to 67.3% in Summer 2021 and 69.8% in Fall 2021. This return to the workforce in late 2021 suggests the restart of the economy and return to a potential "new normal", as seen in Table 5-4.

TABLE 5-4: PANEL EMPLOYMENT STATUS THROUGHOUT THE PANDEMIC (N=162)

	Pre-COVID		Fall 2020		Summer 2021		Fall 2021	
Work Full-Time	116	71.6%	104	64.2%	109	67.3%	113	69.8%
Work Part-Time	15	9.3%	14	8.6%	14	8.6%	16	9.9%
Retired	22	13.6%	21	13.0%	25	15.4%	25	15.4%
Full-Time Student	2	1.2%	3	1.9%	1	0.6%	2	1.2%
Part-Time Student	0	0.0%	2	1.2%	1	0.6%	0	0.0%
Homemaker / Unpaid Caregiver	5	3.1%	7	4.3%	4	2.5%	3	1.9%
Unemployed	2	1.2%	11	6.8%	8	4.9%	3	1.9%

Change in Employment

	Pre-COVID to Fall 2020		Fall 2020 to Summer 2021		Summer 2021 to Fall 2021	
No Change	136	84.0%	139	85.8%	146	90.1%
Out of Workforce *(e.g. changed to unemployed, retired, homemaker, student)*	15	9.3%	6	3.7%	3	1.9
Entered Workforce *(e.g. changed to work)*	5	3.1%	6	3.7%	8	4.9%
Changed Roles within Workforce *(e.g. changed from part-time to full-time)*	6	3.7%	11	6.8%	6	3.7%

5.2.2.2. Personal Attitudes and Opinions

Beyond demographic characteristics, the panel survey recorded respondents' interest in COVID-19 vaccines. Almost all of the panel (97.5%) reported that they had received the COVID vaccine. Of the vaccinated respondents, 17.1% reported that they had already received a booster shot by October 2021, 73.4% were interested in the booster shot, and 9.5% reported that they were not interested in getting a vaccine booster shot. A significantly higher proportion of the panel was reported as vaccinated than the general Atlanta population; Fulton County reported only 60% of its residents had received at least one vaccination dose by October 2021 (Georgia Department of Public Health, 2022). This comparison was potentially limited as reported vaccination numbers may not fully capture the true vaccination rate; people that crossed state lines for a vaccine were not reported in the Georgia records.

High vaccination compliance within the panel and widespread vaccine availability in Georgia did not directly result in lower risk perception due to the pandemic for all respondents; a third of respondents still disagreed or strongly disagreed that "now that a vaccine is available", they were less afraid of COVID-19. Five additional COVID-19 attitude questions were included in the Wave 2 survey, as seen in Figure 5-2. Results from these Likert-style statements indicated that while the majority of respondents (69%) disagreed or strongly disagreed that they had already returned to a "new normal" in the Summer of 2021 when COVID-19 cases were low, the majority (55%) agreed or strongly agree that they expected to return to "normal" by the Fall of 2022. More than a third of respondents (35%) neither agreed nor disagreed that they were expecting to return to a “new normal” in fall 2022; This may suggest a true neutral attitude or uncertainty towards future activities.

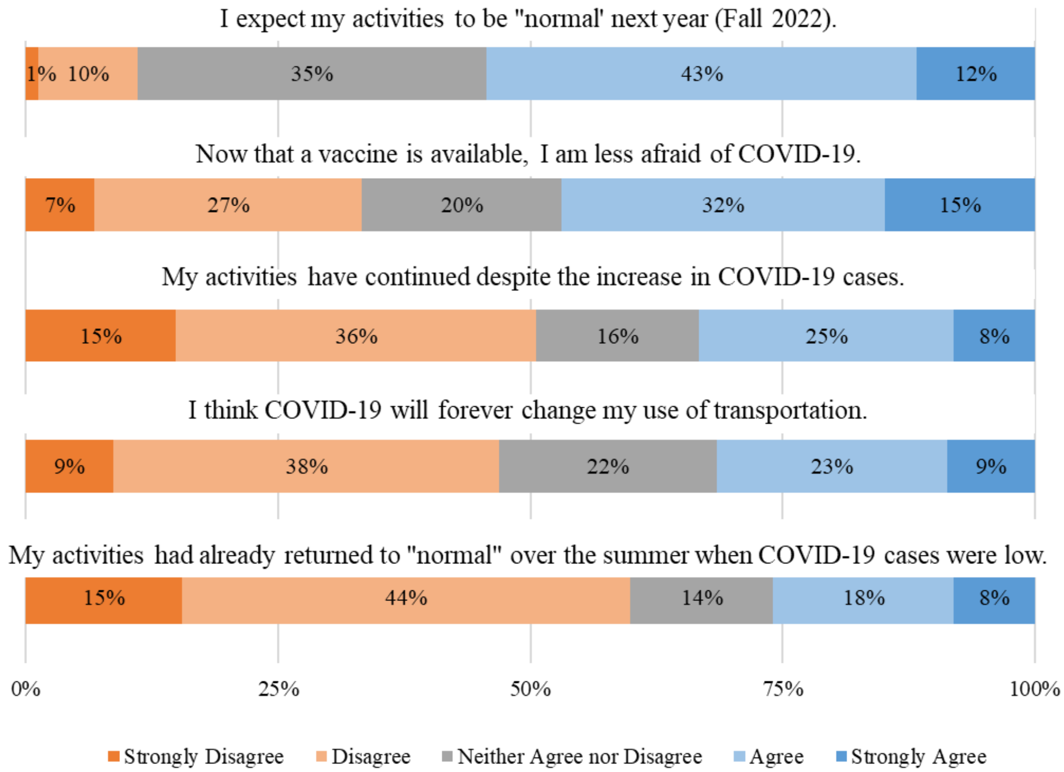


FIGURE 5-2: COVID-19 ATTITUDINAL STATEMENTS (N=162)

As individual attitudes can be important when predicting behavior, the Wave 1 and Wave 2 surveys included fifteen shared attitudinal (five-point) Likert-scaled statements as displayed in Table 5-5. Respondents who did not change their attitude between periods were designated “exactly matching”, and if they gave the same or adjacent answer, were designated “exactly or almost matching”. A Wilcoxon signed-rank test was performed on each attitude to determine if the observed difference between both measurements was significant. The attitudes related to the safety measures implemented by shared mobility services during the pandemic changed between the two waves. In Fall 2020, respondents strongly agreed or agreed that these measures like masks and sanitation would help them feel comfortable on shared transportation but a year later, fewer respondents agreed with the effectiveness of these measures. During the time in between survey waves, armed with the vaccine and newly learned information about the transfer of the disease, respondents may have felt less concern with the risks or felt that these measures were ineffective. Social attitudes also changed between Fall 2020 and 2021. Respondents were slightly less sociable, more uncomfortable around strangers, and enjoyed chatting with strangers less in the post-pandemic world. This may have been due to a prolonged lack of social interaction as a result of distancing and isolation measures [12-13]. Although the pandemic resulted in attitude changes, attitudes related to germ-awareness (A2 and A4) and trust in transit during the pandemic (A9 and A10) remained relatively stable over the year. Similar research indicated that attitudes related to the danger of COVID-19 were relatively stable over six months [14].

TABLE 5-5: RELIABILITY OF INDIVIDUAL ATTITUDINAL STATEMENTS BETWEEN SURVEY WAVES (N=162)

	Fall 2020		***Fall 2021***					
	Average	*SD*	*Average*	*SD*	*Mean Difference*	*% Exactly Matching*	*% Exactly or Almost Matching*	*Sig.*
A1. Sociable	3.99	0.82	3.83	0.92	- 0.154	61.1	92.6	**
A2. Germ-conscious	3.14	1.03	3.15	1.00	+ 0.012	51.9	91.4	-
A3. Uncomfortable around strangers	2.80	1.00	2.94	1.07	+ 0.148	46.3	81.5	*
A4. Carries hand sanitizer	3.11	1.42	3.00	1.44	- 0.111	53.7	82.1	-
A5. Enjoys chatting with driver	3.48	1.03	3.25	1.00	- 0.228	53.1	91.4	***
A6. Enjoys chatting with passengers	2.80	0.97	2.44	1.02	- 0.352	46.9	85.2	***
A7. Uncomfortable on transit with masked passengers	3.99	1.08	2.85	1.04	- 1.148	46.3	82.1	***
A8. Masks should be required on transit	4.86	0.60	4.63	0.91	- 0.228	80.9	96.3	***
A9. Trusts transit agency COVID measures	3.32	1.00	3.32	1.01	+ 0.111	48.2	92.0	-
A10. Transit should be suspended	1.63	0.73	1.40	0.71	- 0.225	64.7	97.0	-
A11. Comfortable on ride-hailing with sanitizing	2.95	1.19	3.36	1.08	+ 0.407	39.5	75.9	***
A12. Would request new ride-hail if driver had no mask	4.44	0.86	3.80	1.19	- 0.642	40.7	80.9	***
A13. Ride-hailing with open windows is worth it	4.20	0.89	3.93	0.87	- 0.278	46.3	90.1	**
A14. Comfortable on shared ride-hailing if passengers wore masks	1.99	0.99	2.63	1.10	- 0.562	35.8	77.2	***
A15. Share ride-hailing should be suspended	3.00	1.29	2.47	1.19	- 0.154	32.1	70.98	***

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree or Agree, 4 = Agree, 5 = Strongly Agree
Wilcoxon Signed-Rank Test on the difference between the two measurements: *** p-value < 0.001, ** p-value <0.01, * p-value < 0.05

An exploratory factor analysis considered eighteen five-point Likert-scale ordinal variables related to the pandemic, shared mobility, and general attitudes. Exploratory factor analysis solutions with 1 to 6 factors were considered. Items with weak loadings, poor interpretability, and high uniqueness were considered for removal. To construct an underlying factor that can explain the interrelationships among observed attitude variables, a Kaiser-Mayer-Olkin (KMO) measure was used to check the sampling adequacy. For factor rotation, the varimax rotation technique was applied as there was only minimal correlation between latent constructs when oblique rotation was tested. The final single (rotated) factor loading matrix explained three factors by ten statements as presented in Table 5-6.

TABLE 5-6: FACTOR LOADINGS MATRIX FOR WAVE 2 COVID ATTITUDES

Factor Loadings for Attitudes	Factor 1	Factor 2	Factor 3
My current activities continue despite the increase in COVID cases.	0.795		
My activities had already returned to "normal" over the summer when COVID cases were low.	0.794		
Wearing a mask should be required for all passengers riding public transit.	-0.775		
If my ride-hailing driver wasn't wearing a mask, I would request a new vehicle.	-0.603	0.444	
Now that a vaccine is available, I am less afraid of COVID.	0.475	-0.506	
Transit service should be suspended until COVID-19 is no longer a major threat.		0.786	
I think COVID-19 will forever change my use of transportation.		0.700	
I'm uncomfortable being around people I don't know.		0.489	-0.614
I consider myself to be a sociable person.			0.757
I enjoy chatting with fellow passengers in a shared ride-hail.			0.647

The three resulting factors explained 60.1% of the variance among the ten variables. The resulting factors were described as "Vaxxed and/or Relaxed", "Pandemic Mindset", and "Extrovert". The "Vaxxed and/or Relaxed" factor explained an attitude where regular activities and behaviors resumed when a vaccine was available (or, independently of whether a vaccine is available). The "Pandemic Mindset" attitude captured a high-risk perception of the ongoing pandemic and infection despite the availability of a vaccine. The final factor, "Extrovert", explained the positive attitude toward interacting with strangers.

5.2.2.3. Frequency of Non-Shared Transportation Usage Over Time

Respondents' transportation behavior was collected for four time periods by asking two sets of survey questions in each wave, one set on current usage and one set on recent past usage. These four questions captured modal usage before the pandemic, in Fall 2020, in Summer 2021, and Fall 2021. Respondents were asked to select a usage frequency category for ten transportation modes and four trip-replacing technologies. These usage frequencies were converted into the approximate monthly frequencies shown in parentheses:

- Never (0)

- Less than once a month (0.5)
- 1-3 times a month (2)
- 1-2 times a week (6)
- 3-4 times a week (14)
- 5 or more times a week (25)

For each mode, paired t-tests of usage frequency were conducted between periods to indicate a significant change in usage. The frequencies were grouped into three categories and compared at each period: Non-Users indicated that they had never used a mode, Occasional Users indicated that they used a mode around a few times a month, and Active Users indicated they used a mode at least once a week.

The vast majority of the panel respondents (86%) used a single-occupancy vehicle at least once a week prior to the pandemic, seen as “active users” in Table 5-7. During the Fall 2020 period, there were fewer respondents that used a single-occupancy vehicle at least once a week than prior to the pandemic. This decrease in private vehicle usage by half of the panel, as seen in Table 5-8, was likely due to the reduced travel, shelter-in-place, and work-from-home policies encouraged by the pandemic. Social distancing policies ended in the state of Georgia in May 2021 so there was a significant increase in private vehicle travel between Fall 2020 and Summer 2021. No major changes in the monthly frequency of usage occurred for private vehicles after this “new normal” was reached in Fall 2021. Significant mean differences were found between pre-COVID and October 2020 with October 2021 monthly frequency usage in private vehicles. The sample’s average monthly usage of personal vehicles (alone) prior to the pandemic was 16.997 times per month, Fall 2020 was 10.593 times per month, and Fall 2021 was 13.472 per month. As stay-at-home restrictions in the initial wave of the pandemic were encouraged, private vehicle usage (both alone and shared) was impacted by the s. Looking at the longer-term impact, 37% of the panel recorded a net decrease in private vehicle (alone) usage when October 2021 levels were compared with pre-pandemic levels. This was likely due to the increased acceptance of teleworking and other trip-replacing technologies that occurred during the pandemic.

Unlike other studies that reported increased usage of active modes during the pandemic, the panel did not exhibit any large increases in their active modal monthly frequency at the start of the pandemic. This difference may be due to a later data collection period that didn’t capture the initial increase of people walking to get out of their homes during peak stay-at-home orders (Conway et al., 2020), different urban environments that may be more friendly to walking (Monterde-I-bort et al., 2022; Scorrano & Danielis, 2021), or the wording of the question collecting only transportation trips, not recreational trips. A significant decrease of

Table 5-7: Usage of Non-Shared Transportation Modes (n=162)

	Mean	S.D.	Active User	Occasional User	Non-User
Private Vehicle (Single Occupant)					
Before COVID	16.997	9.510	86%	9%	6%
Fall 2020	10.593	8.685	77%	17%	6%
Summer 2021	13.327	9.311	82%	12%	6%
Fall 2021	13.472	9.357	83%	9%	7%
Private Vehicle (Multiple Occupants)					
Before COVID	8.922	8.513	64%	31%	5%
Fall 2020	4.843	6.516	40%	39%	22%
Summer 2021	6.660	7.297	51%	38%	11%
Fall 2021	6.271	6.959	48%	39%	13%
Walk					
Before COVID	13.910	4.037	73%	23%	4%
Fall 2020	13.028	10.051	73%	15%	12%
Summer 2021	13.744	9.863	74%	21%	5%
Fall 2021	12.614	9.969	72%	19%	10%
Bicycle					
Before COVID	2.839	6.525	15%	30%	54%
Fall 2020	2.537	6.214	16%	17%	67%
Summer 2021	2.513	6.097	17%	19%	64%
Fall 2021	2.528	6.033	17%	17%	65%
E-Scooter					
Before COVID	0.185	0.737	1%	15%	84%
Fall 2020	0.009	0.067	0%	2%	98%
Summer 2021	0.031	0.182	0%	4%	96%
Fall 2021	0.012	0.078	0%	2%	98%

Never (0), Less than once a month (0.5), 1-3 times a month (2), 1-2 times a week (6), 3-4 times a week (14), 5 or more times a week (25)

Table 5-8: Change in Usage of Non-Shared Transportation Modes (n=162)

	Pre-COVID → Fall'20	Fall'20 → Summer'21	Summer'21 → Fall'21	Pre-COVID → Fall'21	Fall'20 → Fall'21
Private Vehicle (Single Occupant)					
Decrease	50.0%	17.9%	13.0%	37.0%	16.0%
No Change	40.1%	42.0%	74.1%	50.0%	45.1%
Increase	9.9%	40.1%	13.0%	13.0%	38.9%
	***	***		***	***
Private Vehicle (Multiple Occupants)					
Decrease	25.9%	17.9%	21.6%	51.2%	21.0%
No Change	35.8%	37.7%	64.2%	30.2%	36.4%
Increase	4.9%	44.4%	14.2%	18.5%	30.9%
	***	**		**	***
Walk					
Decrease	24.1%	25.9%	21.0%	34.6%	32.1%
No Change	58.0%	44.4%	74.7%	41.4%	43.2%
Increase	17.9%	29.6%	4.3%	24.1%	24.7%
			***		

TABLE 5-9: CONTINUED	Pre-COVID → Fall'20	Fall'20 → Summer'21	Summer'21 → Fall'21	Pre-COVID → Fall'21	Fall'20 → Fall'21
Bicycle					
Decrease	21.0%	13.0%	9.9%	25.3%	13.0%
No Change	73.5%	71.0%	87.0%	59.3%	70.4%
Increase	5.6%	16.0%	6.8%	15.4%	16.7%
E-Scooter					
Decrease	14.8%	0.6%	2.5%	15.4%	2.5%
No Change	85.2%	96.3%	96.9%	83.3%	96.9%
Increase	0.0%	3.1%	0.6%	1.2%	0.6%
	**				**

Paired t-test: * $p < 0.05$, ** $p< 0.01$, *** $p < 0.001$

5.2.2.4. Frequency of Trip Replacing Technology Usage Over Time

To adapt to limitations on travel due to COVID-19 restrictions, a number of technologies were embraced by the general population to replace in-person events including teleworking, online shopping, food delivery, and video calling. Before the pandemic, these technologies were already available and slowly becoming more prevalent. Stay-at-home orders and other disruptive COVID-related protocols forced many people to experiment with virtual technologies for the first time. In both waves of the survey, respondents were asked, "**In the past month**, how often did you use the following technologies instead of making a trip?" In principle, then, these results do not describe the total usage of such technologies, but rather their usage as a trip replacement.

Before COVID-19, almost half of the panel had never teleworked (45%) as displayed in Table 5-9. A few months later in Fall 2020, 67% of the panel were teleworking at least once a week instead of making a trip. Although there was a slight drop in teleworking usage between Fall 2020 and Summer 2021 (30% of the panel decreased their frequency of usage), the behavior seems to be persistent going forward, as almost 60% of the panel reported an increase in teleworking between before and after (Fall 2021) the pandemic, as displayed in Table 5-10.

In addition to the emergence of teleworking as a potentially long-lasting technology trend, the use of video calls to replace in-person meetings has also dramatically increased during 2020 and 2021. Prior to March 2020, less than ten percent of the panel used video calling like Zoom and Teams at least once a week to replace a typical trip. Usage of video calling as a trip replacement peaked in the fall of 2020 but 46.9% of the panel reported an increase in video call usage compared to their pre-COVID levels. The panel increased usage of online shopping and food delivery during the pandemic but declined almost to pre-pandemic levels in the "new normal".

TABLE 5-10: USAGE OF VIRTUAL ACTIVITY TECHNOLOGIES (N=162)

	Mean	S.D.	Active User	Occasional User	Non-User
Telework					
Before COVID	4.037	7.517	27%	28%	45%
Fall 2020	14.734	11.327	67%	8%	25%
Summer 2021	11.969	10.966	65%	10%	25%
Fall 2021	11.500	10.886	61%	12%	27%
Online Shop					
Before COVID	4.833	6.275	38%	55%	7%
Fall 2020	6.796	7.425	54%	43%	4%
Summer 2021	6.920	8.097	50%	39%	11%
Fall 2021	5.762	7.435	41%	45%	14%
Food Delivery					
Before COVID	1.481	2.539	9%	43%	48%
Fall 2020	2.290	4.396	19%	38%	44%
Summer 2021	2.472	5.036	17%	38%	44%
Fall 2021	2.086	4.385	16%	34%	50%
Video Call					
Before COVID	1.296	3.636	9%	38%	54%
Fall 2020	5.957	7.281	46%	40%	15%
Summer 2021	5.027	7.871	32%	41%	27%
Fall 2021	3.827	6.616	25%	40%	35%

Never (0), Less than once a month (0.5), 1-3 times a month (2), 1-2 times a week (6), 3-4 times a week (14), 5 or more times a week (25)

TABLE 5-11: CHANGE IN USAGE OF VIRTUAL ACTIVITY TECHNOLOGIES (N=162)

	Pre-COVID → Fall'20	Fall'20 → Summer'21	Summer'21 → Fall'21	Pre-COVID → Fall'21	Fall'20 → Fall'21
Telework					
Decrease	4.9%	30.2%	9.9%	12.3%	32.7%
No Change	36.4%	57.4%	85.8%	27.8%	56.2%
Increase	58.6%	12.3%	4.3%	59.9%	11.1%
	***	***		***	***
Online Shop					
Decrease	4.9%	32.7%	22.2%	30.2%	43.8%
No Change	54.9%	45.1%	71.6%	35.2%	40.7%
Increase	40.1%	6.8%	6.2%	34.6%	15.4%
	***		***		
Food Delivery					
Decrease	12.3%	22.2%	17.3%	16.7%	27.2%
No Change	53.1%	54.9%	78.4%	55.6%	54.9%
Increase	2.5%	22.8%	4.3%	1.2%	17.9%
	***			***	.
Video Call					
Decrease	3.7%	49.4%	29.0%	16.0%	53.7%
No Change	24.1%	30.2%	65.4%	37.0%	31.5%
Increase	78.4%	20.4%	5.6%	46.9%	14.8%
	***		***	***	***

Paired t-test: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2.2.5. Frequency of Shared Mobility Usage Over Time

As the intention for using shared mobility was likely impacted by an individual's prior usage (Thomas et al., 2021), the Wave 2 and Wave 1 survey asked respondents to report their frequency of usage of shared modes. The usage of all shared mobility services dramatically decreased during the pandemic and has yet to recover. Before the pandemic, private and shared ride-hailing services were used a few times a month to travel to an event or gathering; this was reflected in the collected data as the largest type of private ride-hailing user pre-COVID was an occasional user as displayed in Table 5-11. The most dramatic change in usage of private ride-hailing occurred at the start of the pandemic as 84% of the panel reported a decrease in usage. Although private ride-hailing usage slightly increased between the summer and fall of 2021, 72% reported a decline in use when compared to pre-pandemic levels. Shared ride-hailing still had not officially returned to the city of Atlanta by Fall 2021, so the small number of occasional users saw an initial decline in shared ride-hailing usage without a recovery.

Transit usage overall decreased due to the pandemic as displayed in Table 5-12. This declining trend was more severe in rail than in bus services, but this may be due to the fact that more of the active transit users on the panel were rail users as opposed to bus users, pre-pandemic. Rail usage had a significant rebound effect between Fall 2020 and Fall 2021; almost a quarter of respondents increased their usage compared to usage during COVID restrictions. This increase was likely due to the return of choice transit riders as when compared across income levels, respondents with a very high income (annual household income of $150K or more) increased usage more than those of other income levels. The increase in transit usage from Fall 2020 to Summer 2021 may also be due to people resuming commutes in a "new normal" and the fact that MARTA resumed full capacity of services in the spring of 2021.

TABLE 5-12: USAGE OF SHARED MOBILITY MODES (N=162)

	Mean	S.D.	Active User	Occasional User	Non-User
Private Ride-Hail					
Before COVID	1.907	3.228	12%	78%	10%
Fall 2020	0.284	2.036	1%	11%	88%
Summer 2021	0.543	0.933	1%	46%	53%
Fall 2021	0.586	1.667	1%	35%	64%
Shared Ride-Hail					
Before COVID	0.392	0.855	1%	36%	63%
Fall 2020	0	0	0%	0%	100%
Summer 2021	0	0	0%	0%	100%
Fall 2021	0	0	0%	0%	100%
Bus					
Before COVID	1.352	4.622	7%	31%	61%
Fall 2020	0.525	3.409	2%	3%	94%
Summer 2021	0.669	3.465	4%	10%	86%
Fall 2021	0.562	3.412	2%	7%	91%

TABLE 5-13: CONTINUED

	Mean	S.D.	Active User	Occasional User	Non-User
Rail					
Before COVID	4.126	7.814	21%	64%	15%
Fall 2020	0.762	3.621	4%	9%	86%
Summer 2021	1.293	3.883	9%	28%	63%
Fall 2021	1.225	3.967	8%	23%	69%
Public Transit (Bus or Rail)					
Before COVID	4.494	8.164	22%	64%	14%
Fall 2020	1.481	4.320	5%	9%	86%
Summer 2021	0.917	4.091	10%	27%	62%
Fall 2021	1.392	4.382	9%	23%	68%

Never (0), Less than once a month (0.5), 1-3 times a month (2), 1-2 times a week (6), 3-4 times a week (14), 5 or more times a week (25)

TABLE 5-14: CHANGE IN USAGE OF SHARED MOBILITY MODES (N=162)

	Before COVID → Fall 2020	Fall 2020 → Summer 2021	Summer 2021 → Fall 2021	Before COVID → Fall 2021	Fall 2020 → Fall 2021
Private Ride-Hail					
Decrease	84.0%	2.5%	18.5%	72.2%	5.6%
No Change	15.4%	59.3%	72.8%	22.2%	63.6%
Increase	0.6%	38.3%	8.6%	5.6%	30.9%
	**			***	
Shared Ride-Hail					
Decrease	36.4%	0%	0.0%	35.8%	0%
No Change	63.6%	100%	100%	64.2%	100%
Increase	0.0%	0%	0.0%	0.0%	0%
	***			***	
Bus					
Decrease	35.8%	1.2%	6.8%	35.2%	1.9%
No Change	63.6%	89.5%	93.2%	63.0%	93.2%
Increase	0.6%	9.3%	0.0%	1.9%	4.9%
	*	*	*	*	
Rail					
Decrease	79.6%	3.7%	12.3%	66.0%	5.6%
No Change	19.8%	67.3%	80.9%	30.2%	69.8%
Increase	0.6%	29.0%	6.8%	3.7%	24.7%
	***	*		***	
Public Transit (Bus or Rail)					
Decrease	80.2%	3.7%	12.3%	67.3%	12.3%
No Change	19.1%	66.7%	80.9%	28.4%	80.9%
Increase	0.6%	29.6%	6.8%	4.3%	6.8%
	***	*		***	

Paired t-test: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2.2.6. Level of Comfort Using Shared Mobility Over Time

As some shared mobility options were not available during different stages of the pandemic, capturing attitudes towards shared mobility will help us understand the pandemic's impact. During each wave, the survey defined three distinct past, present, and future periods:

- Wave 1: Before COVID – "past period", COVID was not a threat (before March 2020)
- Wave 1: Fall 2020 – "current period" as Wave 1 was collecting responses
- Wave 1: Vaccine Future – "future period" when a COVID-19 vaccine is available
- Wave 2: Summer 2021 – "past period", when COVID cases were low
- Wave 2: Fall 2021 – "current period" as Wave 2 was collecting responses
- Wave 2: Fall 2022 Future – "future period" of Wave 2, a year from now (Fall 2022)

For each of the three shared mobility modes (private ride-hailing, shared ride-hailing, and transit), respondents were asked to select their level of agreement with the statement that they would feel comfortable using that mode. Results of reported levels of comfort throughout the pandemic were displayed in Figure 5-3 in alluvial diagrams for each mode. Each diagram contains column bar charts of the color-organized reported level of comfort for each defined period with the number of cases labeled (panel sample = 162 respondents). The "future" bars were hatched to indicate respondent prediction and potential uncertainty. In between columns were flows that display the changes in attitudes between periods. For example, starting with Figure 5-3a, 114 respondents strongly agreed (dark blue) that they would have felt comfortable using transit before the pandemic. Of those respondents who strongly agreed, 34 changed their attitude to disagree in October 2020 so a pink curve that was slightly more than a quarter of the "strongly agree" base flows from the before Covid-19 column to the "strongly disagree" portion of the October 2020 column.

FIGURE 5-3: LEVEL OF COMFORT USING SHARED MOBILITY OVER TIME

Figure 5-3a: Level of Comfort Using Transit Over Time

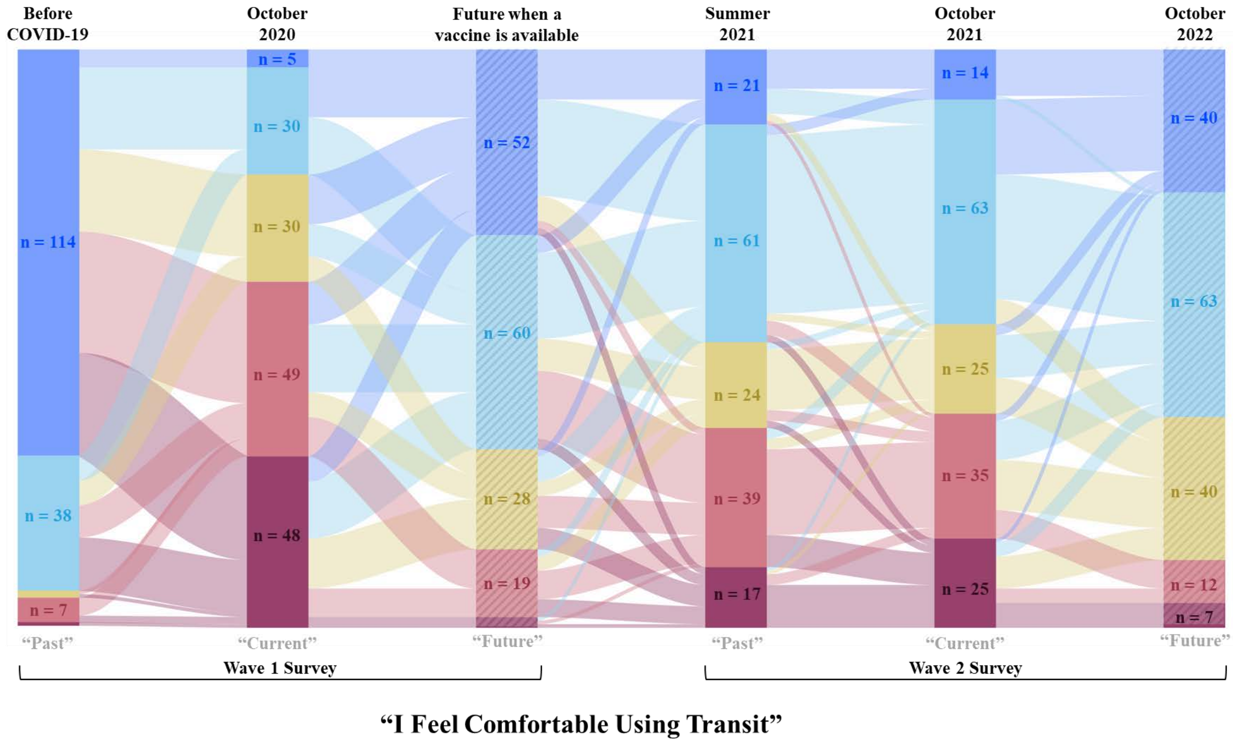


Figure 5-3b: Level of Comfort Using Private Ride-Hailing Over Time

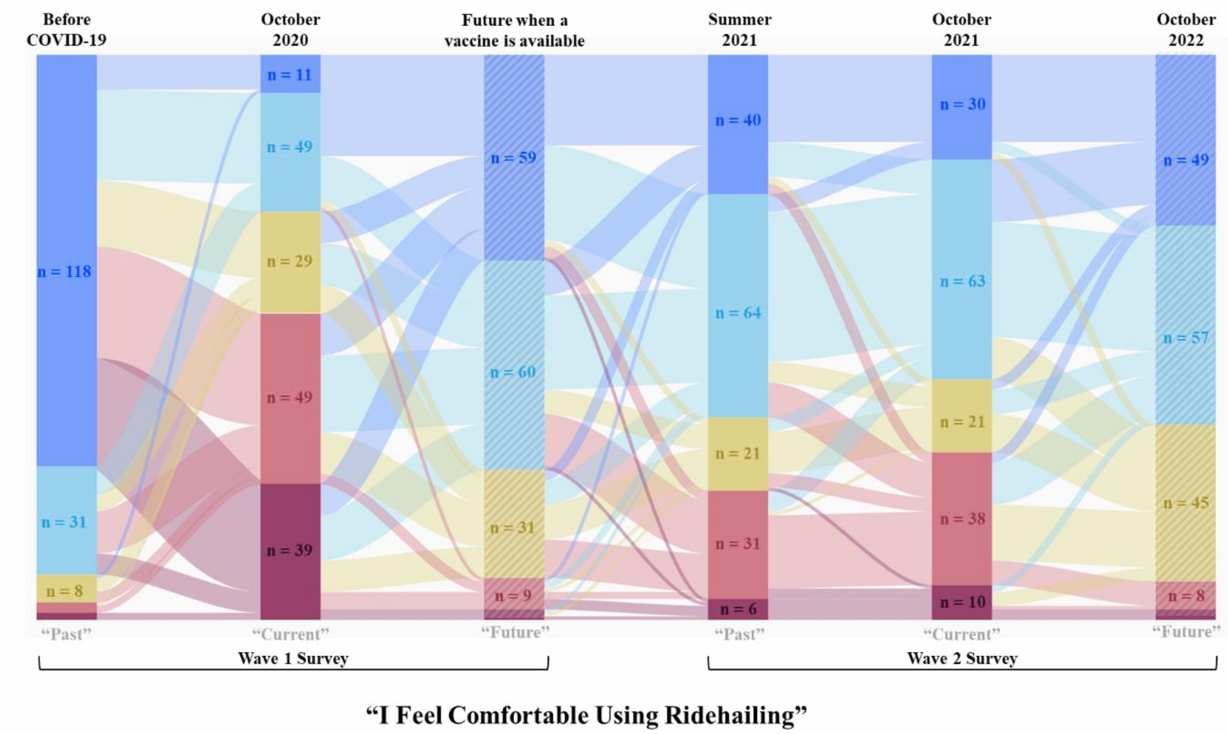
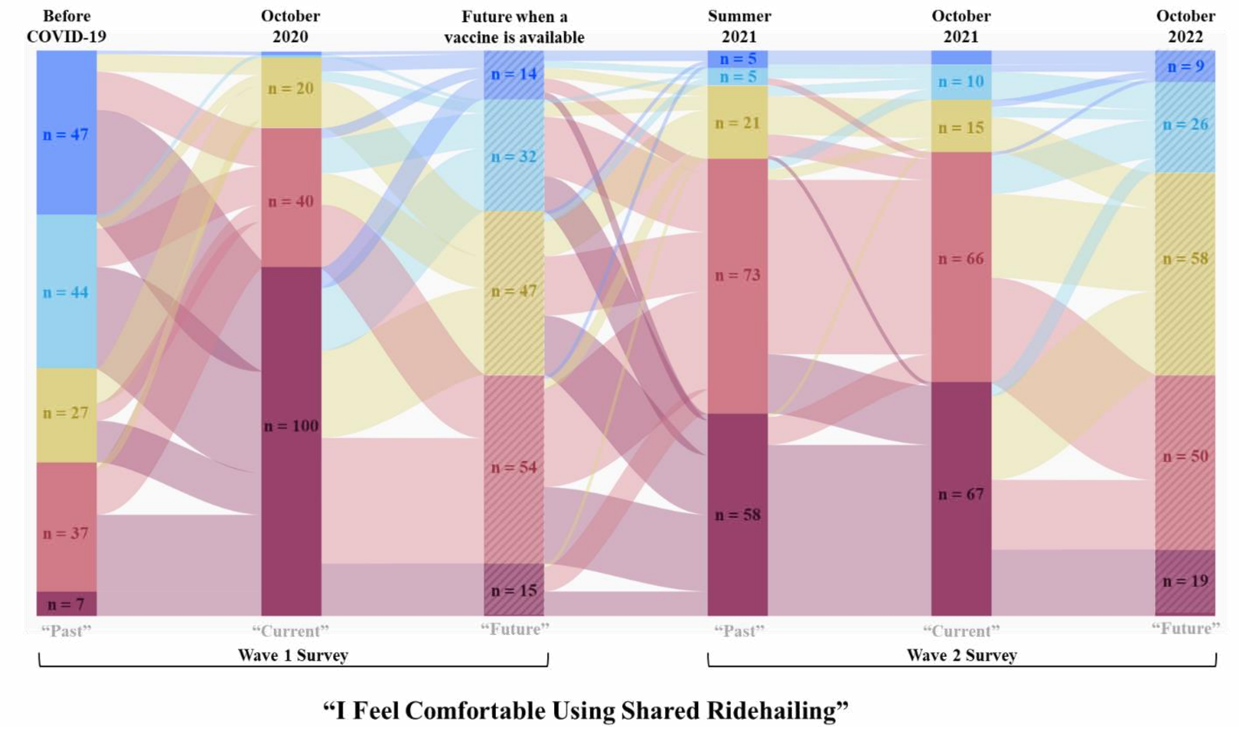


FIGURE 5-3C: LEVEL OF COMFORT USING SHARED RIDE-HAILING OVER TIME



The flow diagrams of Figure 5-3 and Table 5-13 display clear trends of discomfort at the start of the pandemic, with gradual increases in comfort but no return to prior levels of comfort toward shared mobility. The reported levels of comfort with ride-hailing more closely resemble those of transit than of shared ride-hailing; on average respondents agreed that they would feel comfortable using transit and ride-hailing in the periods post-October 2020 but disagreed that they would feel comfortable using shared ride-hailing.

TABLE 5-15: AVERAGE LEVEL OF COMFORT (STANDARD DEVIATION) DURING EACH PERIOD AND AVERAGE CHANGE BETWEEN PERIODS FOR SHARED MODES

Average Level of Comfort (Standard Deviation) During Each Period (n=162)			
	Ride-Hail	**Shared Ride-Hail**	**Transit**
Before COVID	4.604 (0.775)	3.537 (1.247)	4.586 (0.777)
October 2020	2.722 (1.251)	1.537 (0.781)	2.352 (1.177)
Wave 1 "Future"	4.006 (0.975)	2.852 (1.110)	3.858 (1.056)
Summer 2021	3.623 (1.158)	1.926 (0.943)	3.185 (1.237)
October 2021	3.401 (1.208)	1.876 (0.983)	3.037 (1.255)
Wave 2 "Future"	3.870 (0.966)	2.728 (1.046)	3.722 (1.053)

TABLE 5-16: CONTINUED			
Average Change in Level of Comfort (Standard Deviation) Between Periods			
	Ride-Hail	**Shared Ride-Hail**	**Transit**
Pre-COVID → Oct. 2020	- 2.043 (1.420)	- 2.000 (1.445)	- 2.235 (1.273)
Oct.'20 → Summer'21	-1.062 (1.354)	1.315 (1.139)	1.506 (1.176)
Summer'21 → Oct.'2021	-0.222 (0.892)	-0.049 (0.638)	-0.148 (0.836)
Oct.'21 → Oct.'22	0.469 (0.966)	0.852 (0.879)	0.685 (0.949)
1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree / Disagree, 4 = Agree, 5 = Strongly Agree			

Examining the changes in level of comfort using transit, the largest change occurred between the periods of pre-pandemic, when the average respondent strongly agreed, and October 2020, when the average respondent disagreed that they would feel comfortable using transit. In October 2020, 30.3% (49 respondents) of the panel disagreed with feeling comfortable using transit. Of those who disagreed, 38.8% (19 respondents) and 24.5% (12 respondents) predicted that in the future when vaccines were available, they would agree and strongly agree to feeling comfortable in transit, respectively. Although vaccines became available shortly after Wave 1 of the survey, only 14.8% of those who previously agreed that they would feel comfortable using transit with a vaccine actually did report feeling comfortable using transit in the future when vaccines became available. In Wave 2, the majority of the panel (70.4%) did not indicate any change in the level of comfort between Summer 2021 (when cases were slightly higher) and October 2021. Half of the panel indicated that they would likely increase their level of comfort using transit in a year (October 2022).

For private ride-hailing, nearly three-quarters of respondents (72.8%) strongly agreed that they felt comfortable using the service pre-pandemic. This finding reflects that almost all respondents (90%) were occasional or active ride-hailing users before the pandemic. The largest shift in comfort for ride-hailing occurred at the start of the pandemic, between the pre-COVID and October 2020 periods, when 19.2% of the panel changed their level of comfort from "Strongly Agree" to "Strongly Disagree". When asked to predict their future attitude towards ride-hailing when a vaccine is available in Wave 1, only 5.6% of the panel reported the same switch back in the opposite direction (Strongly Disagree to Strongly Agree). In Wave 2, only minimal change in reported comfort occurred between the Summer of 2021 and October 2021; 66% of the panel indicated no change in comfort between the periods. A quarter of the panel indicated that they would increase their level of comfort by a single scale point and 15% indicated that they would increase comfort by two or more scale points in a year (October 2022).

Unlike transit and private ride-hailing, which most respondents felt comfortable using pre-pandemic, shared ride-hailing was not viewed as favorably before COVID. Shared ride-hailing was reported as having the lowest average level of comfort of all three modes during every period recorded. This finding was limited as the majority of the panel had never used shared ride-hailing and this lack of experience may influence attitude towards the mode.

5.3. Results and Discussion

5.3.1. Comparison Between "Future" Comfort Predictions

During both waves of the survey, the panel was asked to predict their future level of comfort using the different shared modes; In Wave 1, respondents were asked to think of the time when a vaccine would be available and in Wave 2, respondents were asked to think of a year from when they were taking the survey (October 2022). Both survey waves captured the panels' attitude toward the "future" of shared mobility but during the year between the survey distributions, more than half of the panel's future attitudes towards shared mobility changed, as displayed in Table 5-14. This difference in predicted future comfort using shared mobility may be due to shifting attitudes or internal inconsistency. Accounting for some human error between responses, similar future attitudes within 1 scale-point accounts for 84%, 76%, and 89% of the panel, ride-hailing, shared ride-hailing, and transit respectively. The large shift in future attitudes related to shared ride-hailing may stem from the panel's lack of experience with the mode.

When comparing the predicted futures from both waves, Wave 2 respondents were less positive about their future willingness to use shared transit than in Wave 1, as seen in the difference of level of comfort averages in Table 5-14; respondents seem to temper their future expectations between Wave 1 and Wave 2. Additionally, their Wave 2 forecasts were less similar to the pre-COVID reported level of comfort, Table 5-13.

An explanation for this less positive view of the future may be that with an extra year of knowledge on COVID, respondents have more realistic expectations of their perceived risk. Respondents may have originally thought that the vaccine would make the risk associated with COVID exposure slim to none, but health experts are predicting a "new normal" endemic COVID that returns in waves.

TABLE 5-17: ATTITUDE TOWARDS THE FUTURE (COMPARISON OF WAVE 1 AND WAVE 2 PREDICTED "FUTURE" LEVEL OF COMFORT)

	Ride-Hail	Shared Ride-Hail	Transit
Same "Future" Prediction	41%	33%	40%
Same or Almost Same "Future" Prediction (Within 1)	84%	76%	89%
Expected "Future" Comfort Declined	37%	37%	35%
Expected "Future" Comfort Increased	22%	30%	25%

TABLE 5-18: CONTINUED

	Ride-Hail	Shared Ride-Hail	Transit
Difference between Average "Wave 2 Future" and Average "Wave 1 Future" Level of Comfort	-0.136	-0.124	-0.136
Difference between Average "Wave 1 Future" and Average Pre-COVID Level of Comfort	1.204	1.666	1.549
Difference between Average "Wave 2 Future" and Average Pre-COVID Level of Comfort	0.735	0.808	0.864

Predicting behavior is difficult for both respondents and researchers. Due to natural projection bias, people tend to exaggerate their future attitudes to better resemble their current attitudes. In addition to projection bias, unrealistic optimism about future events is common. In the era of COVID-19, this was especially important as optimism about future events influences the adoption of self-protective behaviors [15]. Incorrectly predicting the future during times of uncertainty was visible in respondents' reported levels of comfort in Wave 1 and Wave 2.

5.3.2. "Future" Comfort Prediction Precision

In Wave 1, respondents were asked to predict their level of comfort using shared mobility "when a vaccine is available"; at the time of Wave 1, a vaccine was still under development so although this "future" period was unknown, it was likely within the following six months. The vaccine was first available in December 2020 and as of December 2021 half of Georgia's population was fully vaccinated. Wave 2 was collected in October 2021 and respondents were asked to report their current level of comfort. As a vaccine was available at the time of Wave 2, responses should have matched the Wave 1 predicted future, which referenced a time when a vaccine was available. If a respondent's Wave 1 predicted future comfort level (when a vaccine was available) matched their Wave 2 current comfort level (with a vaccine available), they "correctly" predicted their future comfort level. Around one-third of respondents correctly forecasted their future level of comfort between waves as seen in Table 5-15.

TABLE 5-19: PREDICTING FUTURE COMFORT BEHAVIOR (COMPARISON OF WAVE 1 PREDICTED AND WAVE 2 REPORTED LEVEL OF COMFORT)

	Predicted Correct	Predicted Incorrect	Too Positive	Too Negative	Almost Correct (Within 1)
Ride-Hail	41%	59%	43%	16%	81%
Shared Ride-Hail	30%	70%	60%	9%	65%
Transit	31%	69%	55%	14%	73%

Private ride-hailing was more "correctly" predicted than transit and shared ride-hailing. This may be due to prior modal preference as the majority of the panel were occasional or active users of ride-hailing. Unrealistic optimism regarding the comfort of shared modes was present as more participants estimated more comfort than actually reported. Although many respondents were too optimistic about their future comfort during the ongoing pandemic, they were also close to (within one level of) their "correct" comfort, especially for transit and private ride-hailing services. This finding suggests that when using self-reported forecasts of future behavior, collapsing and generalizing attitudes may be more accurate.

To explore the variables that affect the ability to predict future attitudes, chi-square tests were conducted on various socio-demographic variables (i.e. age, gender, race, education, and income), mobility usage (i.e. active, occasional, non-user), and reported levels of comfort. Variables that were found to be significant from these tests were used to build binary logistic regression models predicting the respondents' forecasting type as seen in Table 5-16. These models predicted the probability that an observation falls into one of two categories (e.g. correct prediction or not correct prediction) based on independent variables and displayed the odds ratio to aid in understanding the effects. An incorrect prediction may be An odds ratio that is significantly less than one implies a negative impact of the associated variable on the probability of correctly predicting future attitudes, whereas an odds ratio that is greater than one implies a positive impact. For example, in ride-hailing comfort, on average the odds of correct prediction for women was only 47% of what it was for men, whereas the odds of correct prediction for Gen Xers was 2.6 times higher than they were for others.

The shared ride-hailing comfort predictor included a multimodal indicator which suggested that the odds of correct prediction for multimodal users (e.g. if an individual used a ride-hail, shared ride-hail, transit, bicycle, shared bicycle, or shared e-scooter at least once a week before the pandemic) was only 43% of what it was for non-multimodal users. Interestingly, agreeing with the Wave 1 statement related to comfort using shared ride-hailing in the future impacted the likelihood of correctly predicting attitudes related to shared ride-hailing; the odds of correct prediction for respondents who "Disagreed" that they would feel comfortable using shared ride-hailing in the future with a vaccine, was 1.6 times higher than it was for others.

For transit, having a higher income ($150K or more) decreased the odds of correctly predicting transit usage; the odds of correct transit comfort prediction for high-income respondents was only 40% of what it was for lower income respondents. This finding suggested that "choice" riders in particular were more likely than others to predict that they would have a higher level of comfort when a vaccine was available than they actually did when the vaccine *was* available. Extending "accurate" to include responses that were within 1 scale point produced a model with similar results.

TABLE 5-20: ACCURATE ATTITUDE FORECAST - BINARY LOGIT ODDS RATIOS (OR)

	Ride-Hailing		Shared Ride-Hailing		Transit	
	OR	p-value	OR	p-value	OR	p-value
Socio-Demographic Variables						
Female Indicator	0.469	0.027				
Gen X Indicator	2.563	0.005				
Multimodal Indicator			0.426	0.049		
Higher Income ($150K+) Indicator					0.403	0.020
Wave 1 Future Comfort (ref.: Strongly Disagree)						
Disagree			1.568	0.462		
Neither Agree/Disagree			0.446	0.224		
Agree			0.482	0.009		
Strongly Agree			0.487	0.409		
Constant	0.739	0.304	1.22	0.719	0.606	0.012
LL (intercept-only)	-109.496		-99.297		-97.995	
LL (full)	-103.159		-81.863		-100.910	
Pseudo R2	0.0579		0.1756		0.0289	

5.3.3. Impact of Masks in Shared Spaces

To understand the situational comfort with using shared spaces during the pandemic, participants reported their perceived level of comfort in three shared scenarios -- shared ride-hailing, public transit, and small shared indoor space (e.g. extended elevator ride) -- with and without masks. The Wave 2 survey in October 2021 contained three pairs of statements (with and without masks) rating participants' level of agreement that they would feel comfortable in a shared scenario. The average and standard deviation of reported comfort in each shared space was calculated, as displayed in Table 5-17. Participants felt more comfortable in a small shared indoor space than in scenarios with transit and shared ride-hailing in both the mask and without mask scenarios. A repeated measure ANOVA was performed to compare the level of comfort for each of the three shared scenarios. The null hypothesis was that the level of comfort was the same in the different sharing scenarios. There was a statistically significant effect of sharing scenario on level of comfort, ($F(2,322) = 58.090$, $p<0.005$). A second null hypothesis tested that the level of comfort was the same with and without masks in each shared scenario. A repeated measures ANOVA, with a Greenhouse-Geisser correction to adjust for lack of sphericity, determined that comfort differed significantly between mask and no mask scenarios [$F(1.964, 316.358) = 20.261$, $p<0.005$].

TABLE 5-21: COMFORT WITH AND WITHOUT MASKS IN SHARED ENVIRONMENTS

Comfortable Using…	**Mask**		**No Mask**		Mask – No Mask	
	Average	SD	Average	SD	Average	SD
Small Indoor Space	3.630	0.971	1.876	1.091	+ 1.753	1.110
Shared Ride-Hail	2.630	0.813	1.470	1.103	+ 1.160	1.142
Transit	3.154	0.920	1.524	1.037	+ 1.630	0.984

1=Strongly Disagree, 2= Disagree, 3= Neither Agree/Disagree, 4 = Agree, 5= Strongly Agree

The largest difference in comfort due to masks also was reported in the small shared indoor space scenario. This finding indicates that requiring masks in small indoor spaces will make a slightly larger impact increasing comfort than requiring masks in transit or shared ride-hailing. This may be due to the discomfort of using shared mobility regardless of masking and the sample's limited experiences with shared ride-hailing.

The reported level of comfort of shared ride-hailing with and without masks was further explored through the estimation of a bivariate ordered probit model, summarized in Table 5-18. A variety of socio-demographics and attitudinal explanatory variables were included in the model. An ordered probit was estimated due to the ordinal nature of the dependent variable. A bivariate model was conducted to improve the efficiency of the coefficient estimators by using information from each of the equations to help estimate the parameters of the other equation.

TABLE 5-22: BIVARIATE ORDERED PROBIT MODELS OF COMFORT WITH AND WITHOUT MASKS (N=162)

*Bivariate Ordered Probit Model of Comfort Using **Shared Ride-Hailing***

	No Mask			**Mask**		
	Coeff.	p-value	Sig.	Coeff.	p-value	Sig.
Higher Education Indicator	-0.140	0.965		-0.523	0.049	*
Age Indicator (Boomer)	0.464	0.033	*	-0.376	0.041	*
"Vaxxed and/or Relaxed" Factor	0.656	0.000	***	0.275	0.001	**
Non-User	0.661	0.046	*	0.208	0.485	
α_1	0.727	0.197		-1.677	0.000	***
α_2	1.868	0.000	***	-0.518	0.699	
α_3	2.530	0.000	***	0.199	0.004	**
α_4	3.183	0.000	***	1.176	0.000	***
Correlation Between Error Terms	0.440 ***					
Log-Likelihood (Intercept-only)	342.552					
Log-Likelihood (Full)	341.056					
McFadden Pseudo R2	0.004					

TABLE 5-23: CONTINUED

*Bivariate Ordered Probit Model of Comfort Using **Transit***						
	No Mask			**Mask**		
	Coeff.	p-value	Sig.	Coeff.	p-value	Sig.
Higher Education Indicator	-0.758	0.019	*	-0.132	0.622	
“Vaxxed and/or Relaxed” Factor	1.084	0.000	***	0.552	0.000	***
“Pandemic Mindset” Factor	-0.358	0.003	**	-0.363	0.000	***
“Extrovert” Factor	-0.214	0.047	*	-0.145	0.093	.
Active User	-0.220	0.377		-0.666	0.002	**
α_1	-2.989	0.000	***	-2.165	0.000	***
α_2	1.061	0.000	***	-0.931	0.812	
α_3	1.909	0.000	***	-0.064	0.001	**
α_4	2.989	0.442		1.459	0.000	***
Correlation Between Error Terms	0.552 ***					
Log-Likelihood (Intercept-only)	-304.799					
Log-Likelihood (Full)	-303.301					
McFadden Pseudo R2	0.005					

*Bivariate Ordered Probit Model of Comfort Using **Small Indoor Spaces***						
	No Mask			Mask		
	Coeff.	p-value	Sig.	Coeff.	p-value	Sig.
Non-White Indicator	0.408	0.089	.	0.405	0.077	.
Age Indicator (40+)	0.227	0.332		-0.515	0.022	*
“Vaxxed and/or Relaxed” Factor	0.759	0.000	***	0.484	0.000	***
“Pandemic Mindset” Factor	-0.352	0.001	**	-0.417	0.000	***
α_1	0.218	0.324		-2.674	0.000	***
α_2	1.233	0.000	***	-1.502	0.000	***
α_3	1.813	0.000	***	-0.850	0.000	***
α_4	2.737	0.000	***	0.942	0.000	***
α_1	0.218	0.000	***	-2.674	0.000	***
Correlation Between Error Terms	0.422 ***					
Log-Likelihood (Intercept-only)	-353.370					
Log-Likelihood (Full)	-345.662					
McFadden Pseudo R2	0.022					

Coefficient signs and significance indicate that the achievement of higher education negatively impacts the degree of agreement with feeling comfortable using shared ride-hailing with a mask. The positive coefficient for the age indicator means that the “boomer” generation has a higher degree of agreement with being comfortable using shared ride-hailing without a mask. Finally, the factor of “Vaxxed and/or Relaxed” related to the negative view of masks positively impacts the propensity to agree with riding a shared ride-hail without a mask while also positively impacting the scenario with masks. Error correlations were moderate in magnitude and strongly significant for all three models, indicating sizable amounts of unobserved influences being shared between the no-mask and mask comfort ratings. However, the goodness-of-fit measures for all three models were relatively low, and future work should incorporate more attitudinal variables to improve model fit.

5.4. Conclusion

In this study, the longer-term effects of the pandemic on mobility attitudes were examined to provide important insight into future transportation behaviors and understanding of future attitudes. Respondents in this two-wave panel reported a return to the workforce and an increase in private vehicle usage in late 2021. Although the panel was not representative of the Atlanta population (the panel was older, more highly educated, majority white, higher income, and majority vaccinated), this general trend suggested that the population was moving towards a “new normal” and returning to some pre-COVID behaviors, which has also been suggested by the media [16].

Behavior related to private ride-hailing, shared ride-hailing, and transit had not returned to pre-COVID levels as of October 2021, with the majority of the panel decreasing in usage. Usage of shared mobility did not significantly change during the COVID-19 Delta wave over the summer (between Summer 2021 and October 2021), which indicates that the spread of COVID-19 was not the only factor impacting the use of shared transportation modes. Increased acceptance of technologies, such as telecommuting, that can be used to a replace a trip, will likely prevent the complete return of pre-pandemic levels in shared- and non-shared mobility usage. These conclusions may be limited as the majority of the panel did not use shared ride-hailing and was only an occasional user of ride-hailing and transit prior to the pandemic.

In addition to impacting the behavior of shared mobility, the pandemic resulted in changes to attitudes associated with shared mobility. The initial wave of the pandemic caused significant discomfort in shared mobility scenarios. Although attitudes have improved since the summer of 2021, comfort using transit, ride-hailing, and shared ride-hailing had still not fully returned to pre-pandemic levels. The changes in reported level of comfort of private ride-hailing more closely resembled that of transit than shared ride-hailing. This finding may be impacted by the lack of shared ride-hailing availability during the study period. Future work should examine the relationship between attitudes and behavior to identify the necessary attitudes in order for future intentions to match or exceed pre-COVID usage.

Despite the widespread availability of vaccines in 2021, factor analysis on attitudinal statements identified a high-risk perception associated with COVID attitude, “Pandemic Mindset”. Other latent attitudes uncovered included attitudes “Vaxxed and/or Relaxed”, which explains a lower risk-perception of COVID due to the vaccine, and “Extrovert”, which explains a willingness to meet strangers. This finding highlights the idea that comfort using shared mobility varies with COVID-19 attitudes, even among the vaccinated. In future studies, this work could be conducted outside of the Atlanta area as risk perception varies by built environment and location [17].

Between the two survey waves in 2020 and 2021, many respondent’s attitudes related to safety measures taken in shared mobility, as well as those related to sociability, changed. This contrasts with other studies that have found that attitudes related to COVID-19 and prosociability were relatively stable during the pandemic [14]. Changes to reported levels of agreement on statements related to comfort using shared mobility with safety measures, such as masks and sanitization, indicated that these measures were not as influential in 2021 as they were in 2020. Further analysis on the presence of others wearing masks in a shared space found that masks made the biggest difference in comfort in small indoor spaces and transit. This finding indicated that the presence of masks and proximity to others may not be the limiting factors for comfort in shared ride-hailing. Bivariate ordered probit models revealed that respondents with the “Pandemic Mindset” factor were less comfortable in shared spaces and transit with or without masks. Respondents with a “Vaxxed and/or Relaxed” attitude were more comfortable in shared environments regardless of the presence of masks. As part of the population was wary of returning to shared environments despite masking precautions, shared mobility agencies may need to take precautions other than masking to attract users in “new normal” sharing environments.

The frequent waves and variants of COVID, despite the prevalence of a vaccine, have added even more uncertainty to this disruptive period. The introduction of vaccines was previously predicted to increase comfort levels with the usage of shared modes. Changes in response between periods occurred due to the disruptive and long-lasting nature of the COVID-19 pandemic. A limitation of this study includes the potential random and systematic errors in rating scales that occur over time; response styles, the propensity for a respondent to systematically select item response options, may change with additional knowledge on a topic resulting in a decrease in midpoint and extreme response styles [18]. While comparing attitudes from the October 2020 and October 2021 survey efforts, this study identified differences in respondents’ predicted attitudes for the future and the corresponding attitude in that future period. Unfortunately, most people were incorrectly predicting future attitudes; between the first and second wave of the panel, more than half of the sample were overly optimistic when forecasting their level of comfort using transit and shared ride-hailing services during the pandemic. Binary logistic regression revealed this trend was especially significant for higher income individuals when predicting their transit comfort; these “choice riders” were the least accurate about predicting their level of comfort with using transit in the near future.

6.0. Carving Up the Curb: Evaluating Curb Management Strategies for Ride-Hailing and Ride-Sharing Activity through Simulation

6.1. Introduction

A significant shift of trips from single-occupancy to ride-hailing and ride-sharing has the potential to reduce congestion and longer-term parking demand. This will create both opportunities and challenges in the conversion of typical on-street and off-street parking supply to a variety of flexible uses including pick-up and drop-off zones, development opportunities, or urban green space areas. Cities will need to model and test potential curb management schemes that account for shifting demands from drop-off, pick-up, and waiting activities to prepare for a future of shared vehicles. The development of new methods is required to optimally utilize the curbside, potentially reallocating existing right-of-way to curbside activities or identifying other context-sensitive design changes to address mobility service passenger access and egress.

The goal of this study is to investigate the potential impacts of pick-up and drop-off (PUDO) activities on the curb and adjacent traffic flow by examining existing curb space calibrated to existing behaviors in Atlanta, GA, and model potential curb environment scenarios with increasing levels of PUDO activities. Scenarios establishing priority access to the curb for shared mobility and ride-hailing activities through the designation of PUDO zones are investigated using microscopic simulation. Several curb configurations are devised and tested under varying flow and parking demand characteristics (from low flow and traditional long-term parking demand to high flow and high PUDO share demand). By studying different curb layouts under a wide array of conditions and examining a diverse set of indicators, the effects of specific curb management strategies on curb performance are explored.

6.2. Background

The predominant use of the curb, the public space located between the road and the sidewalk, traditionally has been used for static parking spaces. Curb space has the potential to serve a variety of essential right-of-way functions including mobility, access for people, access for commerce, activation, greening, and vehicle storage [1]. With the rise of ride-hailing and delivery services, a potential solution to the increased curb demand pressure is curbside management which seeks to improve mobility and safety by prioritizing and optimizing curb space [2]. Several tools and treatments, including curb pricing models, geofencing for-hire vehicles, and time limits, are being developed and tested to efficiently reallocate curb space [1-4]. One potential curbside management solution for areas with high passenger pick-up and drop-off (PUDO) activities is to convert existing parking into PUDO-specific zones. By reshaping the curb environment, the curb space has the potential to serve more users and multiple functions.

Future curb demand and resulting curb management strategies are likely to shift with ride-hailing and autonomous vehicle technologies. Ride-hailing vehicles can be a very productive use of curb space as they serve more passengers per minute of curb space occupied than traditional personal vehicles [5]. Although ride-hailing at present trip levels does not eliminate all on-street parking demand, as ride-hailing volumes increase, parking occupancy is expected to decline [7]. Shared autonomous vehicles (SAVs) can further reduce the demand for on-street parking [8-11]. Forecasts with a mixture of autonomous and traditional vehicle types show a reduction in off-street parking demand and a significant increase in curbside loading and unloading demand [12]. To prepare for this spatial shift of demand, cities should consider converting existing static parking to better meet the loading demand of shared mobility [11].

Optimizing the curb's function for passenger loading access can be critical as in-lane PUDO may have significant impacts on traffic flow. Double-parking activity increases with the growth in ride-sourcing [6]. During shorter parking durations like PUDO events, people are less willing to search for curb spots and have a higher likelihood of double parking [13]. The probability of double parking also depends on driver behaviors that vary from city to city and can be impacted by hourly traffic volume, size of commercial area, block length, and number of parking spaces [14], and street width [15]. As vehicles block the flow of traffic, in-lane or double-parking events result in a severe decrease in average speed and an increase in delay and stopped time [16]. In addition to the increased congestion and reduced safety created by double parking, despite reducing circling behavior to identify parking, this behavior may increase emissions overall [17]. To prepare for increased PUDO activities from SAVs and ride-hails, cities should provide more dedicated space on the curbside for short-term parking and short-term loading/unloading.

Multiple cities, including DC, Seattle, and San Francisco, have launched pilot programs to measure and test curbside management strategies to optimize PUDO activities. Outside of the agency and practitioner level, a more limited academic literature attempts to measure and plan for future curbside environments [6,18,19]. A study in Seattle found that the implementation of a passenger loading zone and geofencing strategy reduced the number of pick-ups and drop-offs in the travel lanes and increased curb compliance use [18]. A case study in Gainesville, FL illustrated the effectiveness of PUDO zones and the importance of regulating the number, location, and dwell time of PUDO zones [19]. In California, a study found that increasing the supply of passenger loading space on corridors with high levels of ride-sourcing can reduce the incidence of ride-sourcing vehicles double-parking [6]. Beyond empirical studies based on field surveys, simulation has been used to examine future impacts on the curb. The analysis of multiple VISSIM, a traffic microsimulation tool, scenarios with varying levels of SAV market penetration found dedicated lanes and kiss and ride facilities for PUDO events may result in blockages and turbulence in traffic flow until an SAV market penetration of 25% [20]. A VISSIM study that modeled parking maneuvers with different speeds and number of parking spaces found that the number of parking spaces can be optimized to limit capacity reductions of a road [21]. Simulations of increasing adoption of ride-share services in Lisbon concluded that as ride-sharing adoption increases, the introduction of drop-off zones will result in a smaller impact of traffic fluidity [9]. Despite advancement in the literature of modeling curbside and the increasing number of empirical curb studies, no current study examines the potential traffic and curb impacts from the shift of long-term parking to ride-hailing vehicles while allowing for double parking and on-street parking. This study seeks to fill the gap by examining actual curb and double-parking behavior for passenger loading events at an existing on-street parking environment in Atlanta, GA. This base data is then used to inform the simulation of multiple curb configurations designed to test different levels of curb management through the deployment of dedicated PUDO zones.

6.3. Curbside Data Collection Methodology

In order to calibrate the models, curb activity data was manually processed by reducing video footage into qualitative measures. Video footage from traffic security cameras supplied by a local agency at five locations with high levels of curb activity in the Midtown Atlanta, GA area. The footage of a single location, Spring Street between 8th Street and Peachtree Place, was selected for full video processing due to visibility concerns and on-street parking availability. Spring Street is a three-lane one-way southbound street. This minor arterial runs through a vibrant urban mixed-use district filled with retail and residential uses (e.g. supermarket, restaurants, and high-rise student apartments). As land use and ride-hailing are associated [7], this location appears to fit the profile of a street whose curb environment is set to evolve. This street segment contains paid on-street parking spots on the east (left) side of the street, as seen in Figure 6-1A, and a one-way cycle track on the west (right) side of the street, as seen in Figure 6-1B.

FIGURE 6-1: SPRING STREET BETWEEN 8TH STREET AND PEACHTREE PLACE. 1A) ON-STREET PARKING ON THE EAST (LEFT) SIDE OF THE STREET. 1B) BIKE LANE AND ILLEGAL PARKING ON THE WEST (RIGHT) SIDE OF THE STREET.

On-street parking at this location can be paid at a parking kiosk or through the ParkMobile app and has a maximum limit of four hours. There are two on-street parking zones separated by a curb extension as seen in Figure 6-2; a 90' parking zone for four spaces and a 160' parking zone for seven spaces. The two parking zones resulted in a capacity of eleven on-street parking spots. Some parking spots were not clearly striped so inefficient parking may have resulted in a ten-spot capacity during some periods. Figure 6-2 also identifies two zones where some vehicles stopped in non-dedicated parking places. In the state of Georgia, motor vehicles stopping, standing, or parking on the street side of any vehicle that's stopped or parked at a curb is prohibited [22]. This is known action, known as double parking, occurred on the east (left) side of the street. On the west (right) side of the street next to the cycle track, vehicles also stopped or parked in-lane, which is prohibited within 20 feet of a crosswalk. It is permitted to stop momentarily to pick up or discharge a passenger in this location. Despite the on-street cycle track being physically separated by planters and official signs prohibiting parking on the cycle track, some vehicles slipped through and parked in the inactive curb-pull outs that were used for active construction and being converted to parklets.

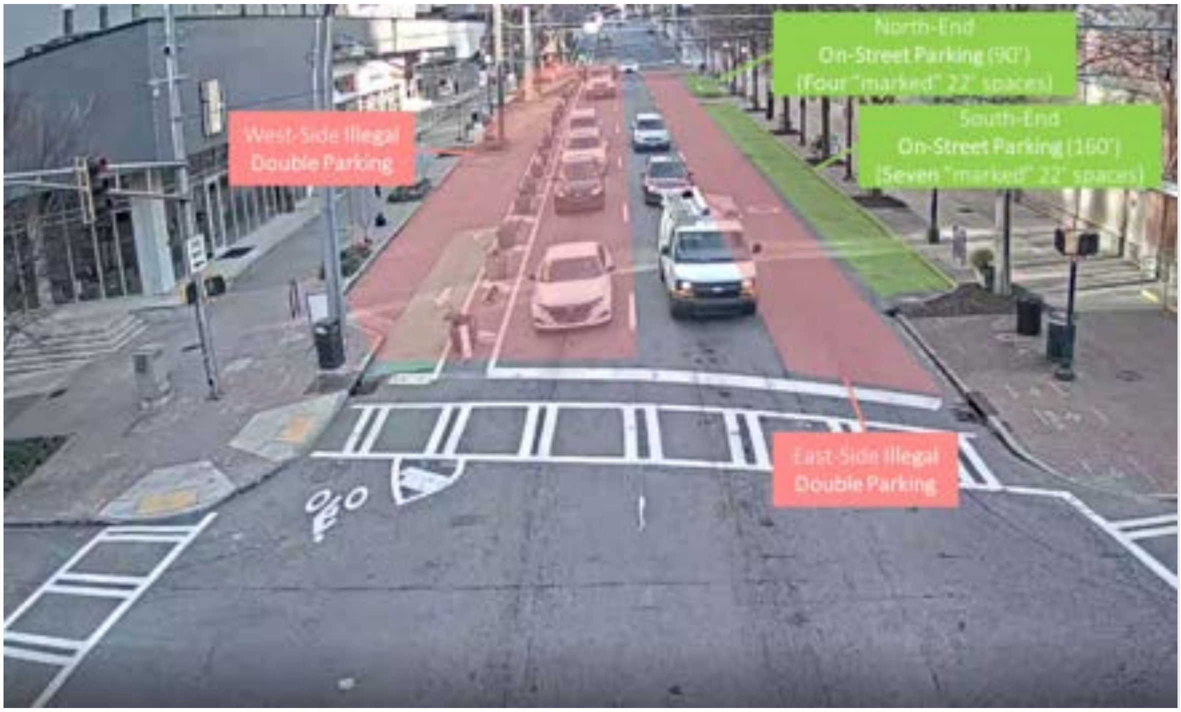


FIGURE 6-2: PERSPECTIVE FROM VIDEO FOOTAGE OF SPRING STREET BETWEEN 8TH STREET AND PEACHTREE PLACE WITH CURB ACTIVITY LOCATIONS LABELED

The analyzed video feed on Spring Street was recorded on Thursday March 3rd, Friday March 4th and Saturday March 12th, 2022 from 8AM to 7PM. Two hours of video (2PM- 3PM and 6-7PM on 3/12/22) were not included in the data due to a video glitch. Video footage was coded by students to capture any parking activity during the observed periods. For each activity, a number of attributes were recorded including the start time, end time, event type (parking, PUDO, or delivery), location zone, indicators for door access, trunk access, and if the driver left the vehicle, number of passengers, vehicle type, parking maneuver (pull-in or parallel park), number of vehicles blocked due to activity, number of weaving vehicles due to activity, and parking availability. If an attribute was too hard to distinguish due to video quality or angle, it was coded NA. After all events were coded, activities with a calculated dwell time under three minutes or over four hours were checked to improve data accuracy.

Additional video data was processed for a section of West Peachtree between 13th Street and 14th Street on Thursday March 3rd, 2022 from 8AM to 7PM to further examine illegal parking behavior. West Peachtree Street is a one-way northbound street with three through lanes, a right turn lane and a left turn lane. Despite lacking dedicated on-street parking, many vehicles stop for extended periods in the left- and right-most lanes to access retail and residential uses (e.g. supermarket, restaurants, and high-rise apartments).

6.4. Curbside Data Analysis and Results

A total of 581 curb activities were recorded on Spring Street during the data collection periods, as seen in Table 6-1. The majority (76%) of the activities that occurred on each day were coded as a parking event, where the driver and/or passengers get out of the vehicle, leave for an extended period, and return. Less than a quarter (14%) of curb activities were coded as a PUDO event, where a passenger gets in or out of the vehicle and then the driver continues onwards. The data collection process only identified a few (3%) delivery events, where a driver or passenger leaves or returns with a package or bag. Not all curb activity was identified with an event type due to footage visibility issues, i.e. the view of passengers and drivers was blocked due to traffic or other vehicles. This introduces a potential bias of collected curb activity as events occurring at the north end of the block, farthest from the camera, were not as visible. At the West Peachtree Location with no on-street parking, 125 events occurred during the day of data collection with around half (52%) as PUDO events.

TABLE 6-1: CURB ACTIVITY BY TYPE ON SPRING STREET

	Spring Street Location				West Peachtree Location
	Thursday 3/3/2022	Friday 3/4/2022	Saturday 3/12/2022	Total	Thursday 3/3/2022
Parked	164 (77%)	141 (68%)	136 (73%)	442 (76%)	17 (14%)
PUDO	31 (15%)	20 (11%)	33 (18%)	83 (14%)	65 (52%)
Delivery	4 (2%)	11 (6%)	3 (2%)	19 (3%)	29 (23%)
NA	9 (4%)	15 (8%)	14 (8%)	38 (7%)	13 (11%)
Total	208 (36%)	187 (32%)	186 (32%)	581	125

The largest number of PUDO events occurred midday from 1-2PM, as seen in Figure 6-3. The probability of a PUDO event occurring was highest (28%) during the morning period 8-9AM. This may be due to a low number of total curb events during the morning. Although this finding differs from other study locations which found the number of PUDO events highest in the evenings [6], the context of the curb and surrounding land use may account for these differences. Additional data collection for longer periods in the evening may draw more conclusive results.

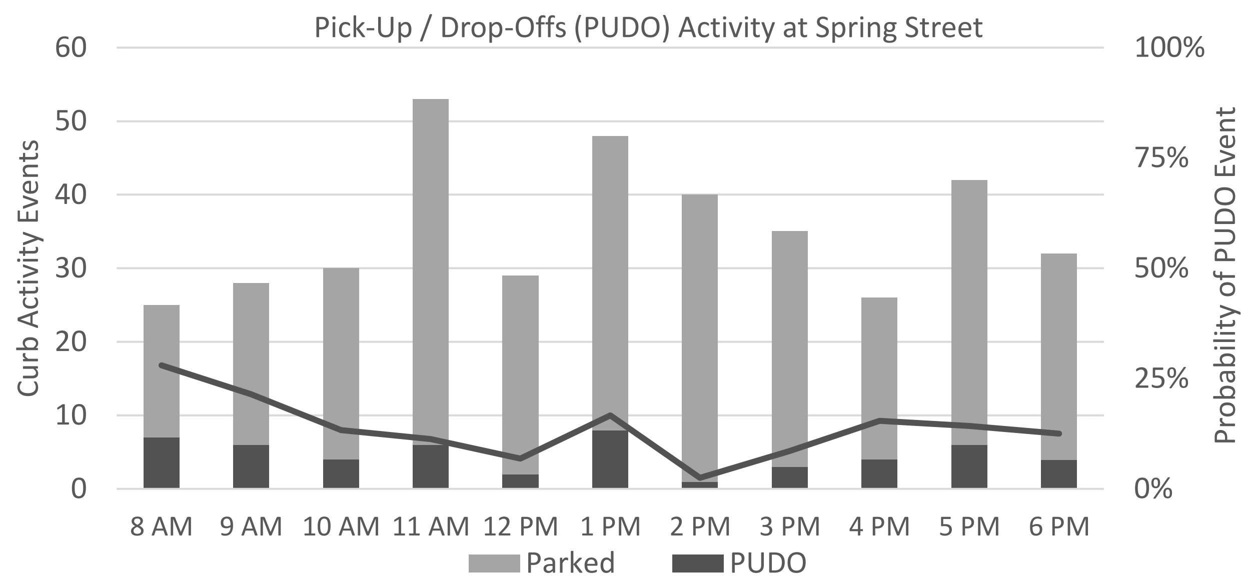


FIGURE 6-3: CURB ACTIVITY AT SPRING STREET BY TIME OF DAY ON MARCH 3 AND 4, 2022

OF THE 83 PUDO EVENTS RECORDED ON SPRING STREET, ALMOST HALF (N=33) DOUBLE-PARKED INSTEAD OF STOPPING ON THE DEDICATED CURB. THE PROBABILITY OF A DOUBLE PARKING PUDO EVENT WAS HIGHEST DURING THE MORNING PERIOD WHEN PARKING AVAILABILITY WAS HIGHEST, AS SEEN IN

Figure 6-4. Regardless of potential spots available for PUDO vehicles, many just momentarily stopped in a lane. This analysis did not record traffic volume throughout the day which may impact the willingness of vehicles to stop in lane.

Percent distribution matrix for the likelihood of PUDO events Double Parking

Parking Availability	**8AM**	**9AM**	**10AM**	**11AM**	**12PM**	**1PM**	**2PM**	**3PM**	**4PM**	**5PM**	**6PM**
0% -25%					0/1		1/1			0/1	
25% - 50%		0/2		2/5	1/3	1/2	5/9	1/2	0/1	2/4	1/2
50% - 75%	4/6	3/5	2/4	1/3	0/2	3/6		2/3	0/5	2/5	0/2
75% -100%	2/6	0/1	1/1							0/1	
Average Parking Availability Per Hour	82%	68%	66%	56%	45%	54%	50%	56%	54%	54%	48%

FIGURE 6-4: PROBABILITY OF DOUBLE PARKING FOR PUDO EVENTS BY PARKING AVAILABILITY AND TIME

Double parking events had a shorter dwell time than on-street events at all curb locations at Spring Street, as seen in Table 6-2. The average dwell time for a PUDO double parking event was under a minute while PUDO events in the dedicated curb space averaged under three minutes. This result of shorter average PUDO and parking dwell times when stopping in the travel lane is consistent with other studies [19]. The majority of events that occurred in the double-parking zone were PUDO events. More double-parking events occurred on the west-side of the street (the space on the opposite side of the dedicated parking space) than on the east-side of the street (the space directly adjacent to the dedicated parking space). This may be due to driver behavior of picking up or dropping off at the spot closest to the sidewalk and most convenient to the passenger’s destination. A similar effect may be seen as north-end on-street parking spaces, closest to the entrance to the grocery store, had higher productivity of 2.73 events per foot of curb over the study period compared with the 1.70 events per foot of curb over the study period on the south-end on-street parking.

TABLE 6-2: SPRING STREET CURB EVENTS BY LOCATION

Zone	Total Events	# Events/ft of curb	# PUDO Events	% PUDO	Average Parking Dwell Time (minutes)	Average PUDO Dwell Time (minutes)
North-End On-Street Parking Zone	246	2.73	34	14%	23.04	2.61
South-End On-Street Parking Zone	272	1.70	16	6%	15.62	1.78
On-Street Parking Zone	518	2.07	50	10%	19.35	2.03
East-Side Double Parking Zone	14	0.06	6	42%	2.27	0.49
West-Side Double Parking Zone	49	0.20	27	55%	2.65	0.76
Double Parking Zone	63	0.25	33	52%	2.56	0.87

The average dwell time for double-parked vehicles was 2.56 minutes while the average dwell time for parked vehicles is 19.3 minutes, as seen in Table 6-2. Double parking events on Spring Street and West Peachtree Street had different dwell times. This suggests a difference in driver behavior for different street types and surrounding uses. Although passenger unloading events had a lower average dwell time, no significant difference was determined between passenger loading and passenger unloading events.

Dwell time was further examined for passenger loading and unloading activities as seen in Figure 6-5. While all unloading events were under three minutes, approximal 20% of loading activities lasted longer than three minutes with the longest loading dwell time of 8.03 minutes. Passenger unloading events (0.69 minutes) had a lower average dwell time than passenger loading events (1.84 minutes).

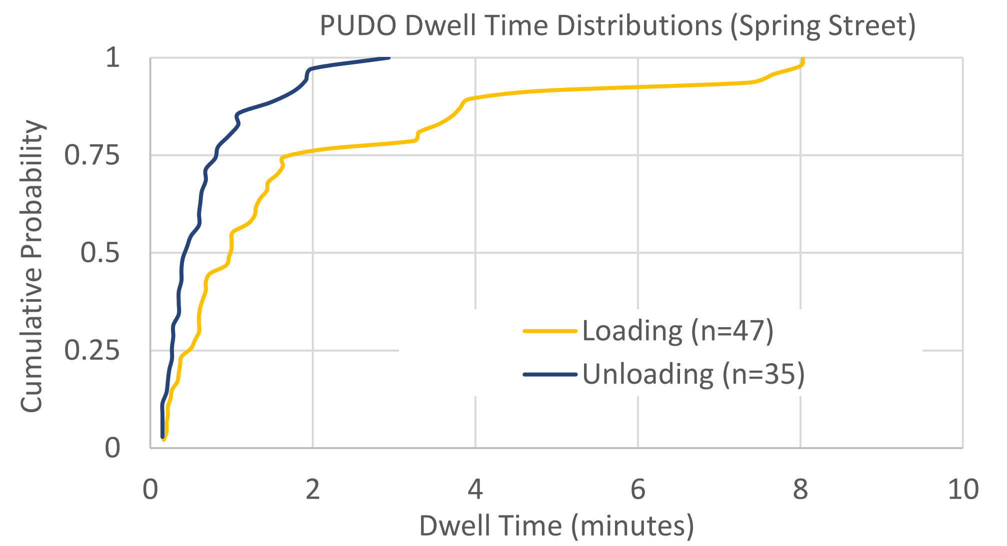


FIGURE 6-5: DWELL TIME CPF FOR PUDOS AT SPRING STREET

The average dwell time for double-parked vehicles was 2.56 minutes, while the average dwell time for parked vehicles was 19.3 minutes (excluding vehicles who parked before the videos started or left after they ended), as seen in Table 6-2. This suggests a difference in driver behavior for different street types and surrounding uses. Vehicles stopping in the dedicated on-street parking followed similar dwell-time distributions, as seen in Figure 6-6. The distribution of dwell times for West Peachtree Street more closely followed that of double-parking events on Spring Street. This may suggest that the presence of longer-term on-street parking increases dwell time.

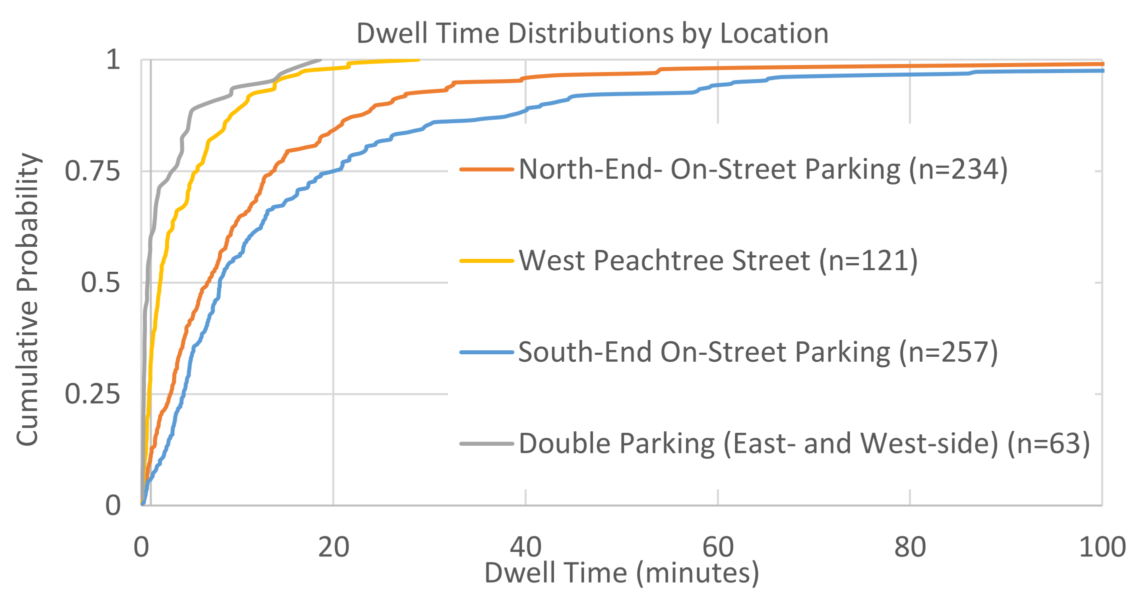


FIGURE 6-6: DWELL TIME CPF BY CURB LOCATION

6.4. VISSIM Modeling Methodology

The video data collection and analysis phase allowed for the calibration of a simulated curb environment using PTV VISSIM software. This modeling software was chosen because it allowed the study of curb performance at the level of individual vehicles, and was capable of outputting a variety of performance measures of interest. The Spring Street field data was used to calibrate the dwell times of vehicles parking at the curb. Two vehicle classes were defined, each with its own curb behavior:

- General passenger vehicles (GPV), with a long-term parking use of the curb from as little as 30 seconds to 8 hours;
- Pick-up and drop-off vehicles (TNCs), with a short-term parking use of the curb generally less than 3 minutes.

A third vehicle class (through vehicles) was defined to measure the effects of changing parking behaviors on non-stopping traffic and congestion.

Since the focus of the study was to understand how different parking needs and types affect the curb environment, a small network was devised (Figure 6). All modeled curb configurations contained three one-way, two-lane links (total roadway length of 1350 ft). Additionally, the central link (link 2) contained on-street parking (modified for each alternative design) adjacent to the right lane. Three vehicle inputs, corresponding to the three vehicle classes, were located at the upstream end of the modeled road segment. During a simulation run, vehicles entering the network were assigned a Static Vehicle Route that would guide them through the entire road segment. Upon approaching the parking spaces, vehicles crossed a “Parking Routing Decision” point (approximately 200 ft upstream of the first parking space), which assigned vehicle parking behavior (i.e., if a vehicle would attempt to park, the length of time parked, and assigned parking space) to those vehicle classes designated to park. After exiting a parking space, vehicles rejoined their Static Vehicle Route. PUDO vehicles also had the option to double park in the right through lane while GPV parking only occurred in spaces located directly adjacent to the curb. To model double parking, a second series of parking spaces was introduced in the right-most lane, directly adjacent to curb parking spaces. Based on field observations, these double-parking spaces were slightly larger (25 ft) than the standard 22 ft curbside parking space. Based on the Spring Street dataset double parking was modeled using an "average likelihood of double parking", estimated based on the PUDO event subset. Out of 83 PUDO events, 33 occurred in the flow of traffic (double parking). Thus, a double-parking likelihood of 40% was assumed for PUDO vehicles. The decision for a PUDO to double was held at 40%, regardless of the available curb parking. This follows the trend observed on Spring St. (Table 1) where the rate of double parking was not found to be correlated with parking availability. Lastly, in all simulations GPV vehicles were set to drive on if a parking space were not available when crossing the Parking Routing Decision point, while PUDO vehicles were set to wait for a space to open up when parking was currently full, whether assigned to curb or double parking.

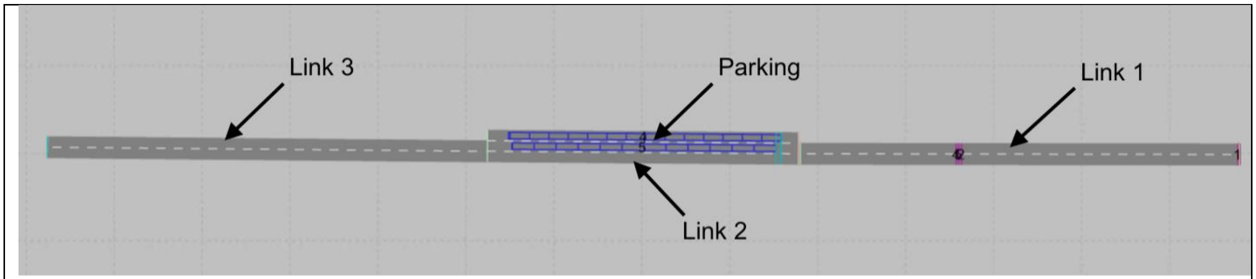


FIGURE 6-7: NETWORK LAYOUT. DIRECTION OF TRAFFIC FROM RIGHT TO LEFT, CURB PARKING ALONG THE MIDDLE SEGMENT.

By varying traffic flow and PUDO ratios (Table 6-3), 13 total demand scenarios were created. Ten replicate runs were completed for each scenario. The average across replicates is report within this effort. Amongst all scenarios, the overall parking event rate was maintained constant at 5% of the traffic flow, except for the base scenario (scenario 1), which reflected current conditions as observed in the field and had a parking rate of 3.2% and a PUDO share of 10%. Each simulation run lasted 4500 seconds, and data was collected only during the last 3600 seconds to allow for a 900 second warm up period.

TABLE 6-3. SCENARIO CHARACTERISTICS

Flow level	*Flow (veh/h)*	*Parking Rate (%)*	*PUDO Share (%)*	*Scenario no.*
Base	1000 veh/h	3.2%	10%	1
Low Flow	1000 veh/h	5%	10%	2
			30%	3
			60%	4
			90%	5
Mid Flow	1500 veh/h	5%	10%	6
			30%	7
			60%	8
			90%	9
High Flow	2000 veh/h	5%	10%	10
			30%	11
			60%	12
			90%	13

In addition to the demand scenarios three distinct curb configurations were devised. These configurations were established to examine the impact of dedicated PUDO zones on curb performance, traffic, and congestion. The 13 scenarios were created by altering the vehicle inputs according to the assigned parking rate and PUDO share. Each scenario was run 10 times for different five curb configurations in a different VISSIM project file. The five curb configurations established to examine the impact of dedicated PUDO spaces. The initial configuration had no dedicated PUDO spaces, Alternative 1.0 and 1.1 had two dedicated PUDO spaces, and Alternative 2.0 and 2.1 had four dedicated PUDO spaces.

6.4.1. Initial Curb Configuration

The initial curb configuration (Figure 6-8) was designed to reflect a typical current curb environment, prevalent in most urban areas across the United States. In such a configuration, parking spaces were open to all vehicle types and (allowed) curb uses, without any distinctions. Along the entirety of the parking lot link, 14 parking spaces were created. In the right-most lane, a double-parking zone was introduced with enough space to allow for 12 vehicles to double park. Taking this into account, in addition to the assumptions and details defined above, the attractiveness of the parking spaces (i.e., likelihood of selecting a specific parking space) was assumed to be uniform. This scenario was devised to act as a control, or baseline, to evaluate the magnitude and scope of the impact of curb the management strategy developed in the alternative curb configurations.

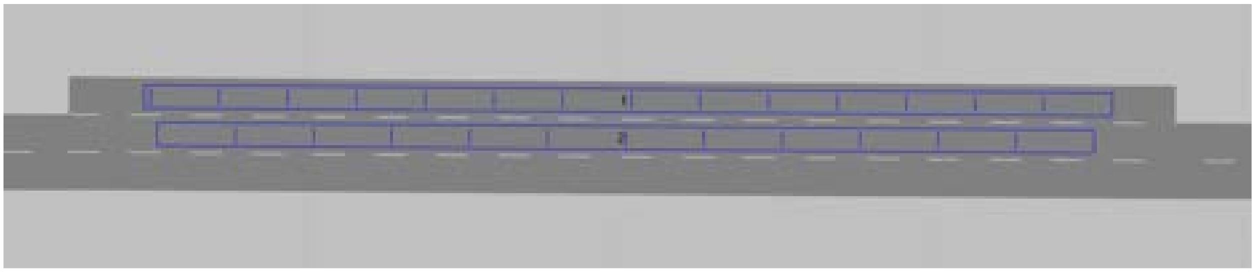


FIGURE 6-8. INITIAL CONFIGURATION, WITH CURBSIDE PARKING (1) AND DOUBLE-PARKING ZONE (2) AND TRAFFIC FLOWING FROM RIGHT TO LEFT.

6.4.2. Alternative 1

Alternative 1 was created to examine the impact of dedicating a limited number of parking spaces for PUDO events. The initial curb configuration was modified by converting two on-street parking spaces from general parking to PUDO only (thus creating two PUDO zones). A significant assumption was then made to configure and modify the rate at which PUDO vehicles were directed to park in the reserved spaces (i.e., the PUDO zone parking rate). It was assumed that if a space within a PUDO zone was available, a PUDO vehicle would be directed to it (100% of the time). This important assumption required a dynamic change in the parking rate associated with the parking routing decision for the PUDO zones, which was obtained in the model through VISSIM's Attribute Modifications feature and was based on the number of parking spaces currently available in the PUDO zones. The PUDO zone parking rate was set to alternate between 0 (for when the zones were full) and 1 (for when the zones were at least partially empty). For PUDO zone parking rate 0 (PUDO zones full), the general vehicle behavior closely resembled that of the base curb configuration (with fewer overall parking spaces available). Operationally, adopting this modeling approach means that the simulations reflect a reality in which designated PUDO zones are significantly more attractive than general parking spaces or that vehicles effectively require PUDO vehicles to use designated zones when available.

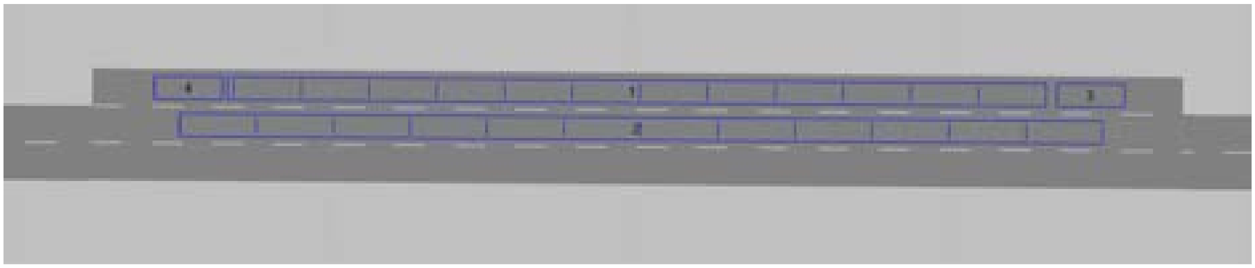


FIGURE 6-9. ALTERNATIVE 1.0 WITH PUDO ZONES (3,4) AT THE END OF THE CURBSIDE PARKING LOT (1)

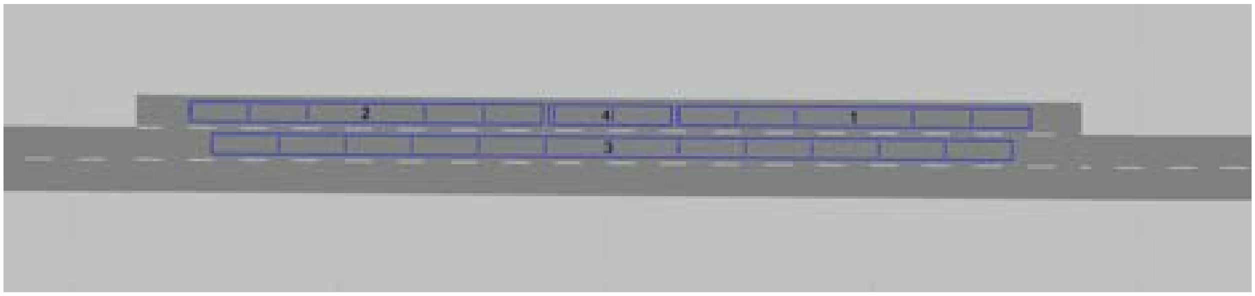


FIGURE 6-10. ALTERNATIVE 1.1 WITH PUDO ZONE (4) AT THE CENTER OF THE CURBSIDE PARKING LOT (SPLIT INTO 1 AND 2)

The first configuration of Alternative 1 (called 1.0) was created by reserving one parking space for PUDO events at each end of the linear parking lot, as displayed in Figure 6-9. This solution was devised as a way to separate different curb uses and parking behaviors while reducing conflicts, delays, and overall travel time. Most of the benefits of such a solution would occur as long as the PUDO zones were not overwhelmed with demand.

The second configuration of Alternative 1 (called 1.1) was created by reserving the center of the on-street linear parking lot for a single mid-block PUDO zone, two parking spaces long, as displayed in Figure 6-10. The main difference between Alternatives 1.0 and 1.1 was purely geometric with PUDO zones at the end of the block or grouped in the center. In terms of future implementation, the two variants could be deployed in different settings: for instance, should field observations show that PUDO events are concentrated mid-block, then Alternative 1.1 should be considered for implementation over Alternative 1.0.

6.4.3. Alternative Curb Configuration 2

To evaluate the impact of different sized PUDO zones on performance metrics Alternative 2, was established. For this alternative, a total of 4 parking spaces were reserved for PUDO parking events. Alternative 2 further reduces the number of parking spaces available for long-term parking events and reallocates the space for PUDO activities. By varying the amount of curb space reserved for PUDO events, changes in curb performance at varying levels of flow and PUDO share was evaluated between the alternatives and configurations. Two configurations of Alternative 2 were created with different locations of the PUDO zones: Alternative 2.0, with two-space PUDO zones at the both ends of the block, and Alternative 2.1, with a single four-space PUDO zone mid-block.

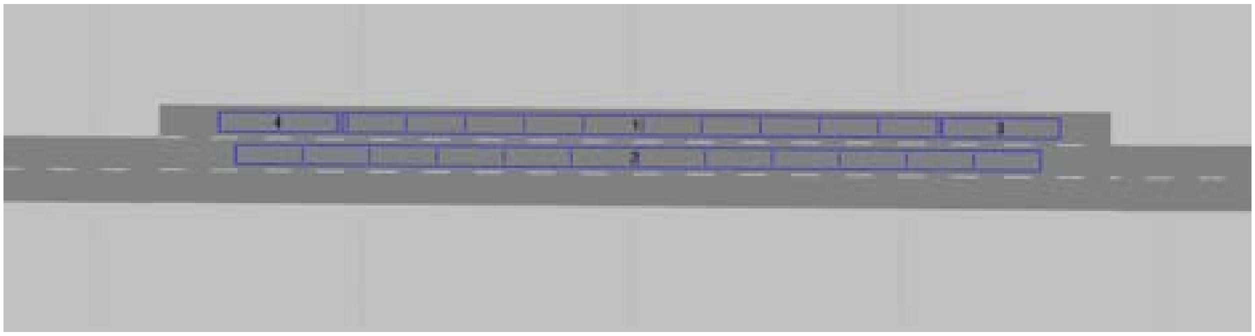


FIGURE 6-11. ALTERNATIVE 2.0 WITH PUDO ZONES (3,4) AT THE END OF THE CURBSIDE PARKING LOT (1)

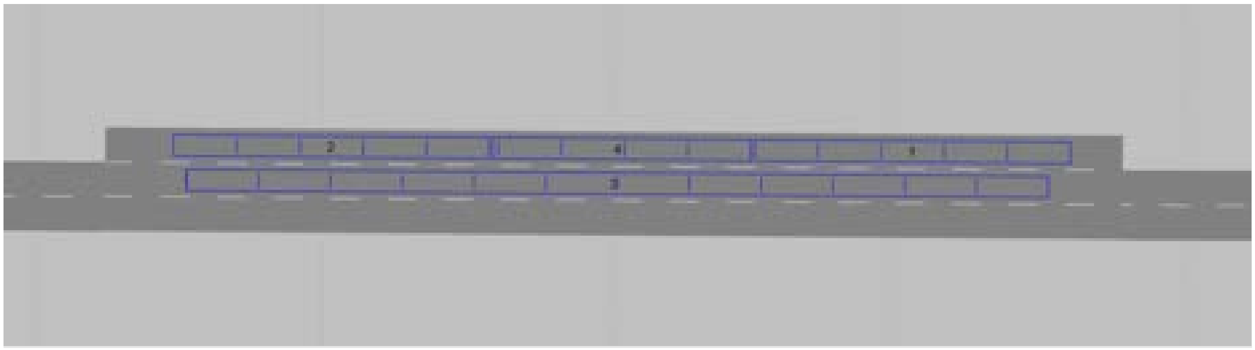


FIGURE 6-12. ALTERNATIVE 2.1 WITH PUDO ZONE (4) AT THE CENTER OF THE CURBSIDE PARKING LOT (SPLIT INTO 1 AND 2)

6.4.4. Modeling issues and assumptions

The 40% PUDO double parking and 100% attractiveness of PUDO zones constituted two critical assumptions with potentially significant impacts on the modeling results. The first assumption was set as no clear relationship between parking availability and PUDO double parking probability was established in the dataset used to calibrate the models. This may be due to limited volume of collected field data, especially at "extreme" conditions of full and empty curbside parking lot. Further data collection and research is needed to determine this complex relationship, which is also impacted by a number of location-based factors (e.g. number of lanes, flow characteristics). A case-based approach (in which a variety of curbs in multiple environments are studied) might be required to reach meaningful results.

Due to the decision to model double-parking behavior assuming of a constant double-parking share of 40%, some PUDO vehicles ended up being directed to the curbside parking spaces even when those spaces were full. In those situations, a 30-second diffusion time was set to simulate the blockage of traffic that occurs when a vehicle, seeing no parking space available, decides to briefly double-park to drop someone off or pick someone up. In other words, when PUDO vehicles were approaching a full parking lot, since they were obliged to wait for a parking space to free up, a fixed 30-second wait time was set to simulate a brief PUDO event. When those 30 seconds passed, the simulation removed the blockage by diffusing (forced removal from the network) the vehicle. This solution was not ideal, as this meant that:

- vehicles diffused did not rejoin traffic (an unrealistic situation)
- no variability in this short curb event could be introduced

Since the data collection phase did not include the implementation of PUDO zones, a modeling assumption regarding the attractiveness of the PUDO zones was required. By setting all PUDO vehicles to stop in one of the dedicated PUDO spaces (if available), the relative attractiveness of a PUDO zone parking space was effectively set to be higher than that of a general parking space and that of double-parking. Unless PUDO vehicles are piloted by an autonomous system that requires compliance, the assumption that human drivers find available PUDO zones significantly more attractive than available long-term spaces might not be accurate. High levels of PUDO zone compliance, as established in this modeling assumption, could be achieved provided:

- correct placement: before implementing any dedicated PUDO zones, a field study should be conducted to determine the best location for each zone
- good enforcement: if double-parking is allowed and not supervised, road users will continue to resort to this behavior
- use of incentives, such as free parking or, for TNCs, reduced rates.

Finally, due to the way in which the parking lot and double-parking spaces were constructed in VISSIM, an unresolved weaving issue was observed. This issue was most evident when PUDO vehicles double-parked adjacent to an empty spot (Figure 6-13), through traffic approaching the parked vehicle would attempt to overtake the obstacle both from the left (correct maneuver) and from the right (incorrect, or unrealistic, maneuver). Due to the nature of the metrics used to evaluate the curb configurations, this issue, though evident in the simulation visualization, did not have a significant impact on the results since:

- in most scenarios, the number of vehicles double parking was limited
- vehicles resumed similar behavior downstream of the parked vehicle

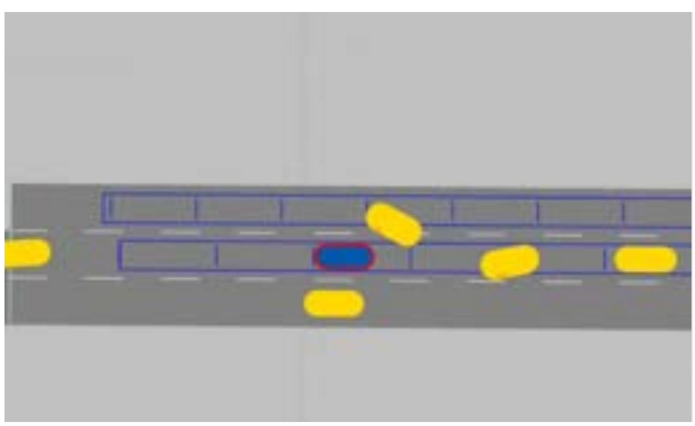


FIGURE 6-13. WEAVING ISSUE ENCOUNTERED DURING SIMULATION, WHERE THROUGH VEHICLES PASSED DOUBLE-PARKED VEHICLES BOTH ON THE LEFT AND ON THE RIGHT (USING EMPTY CURBSIDE PARKING SPACES AS AN ADDITIONAL LANE).

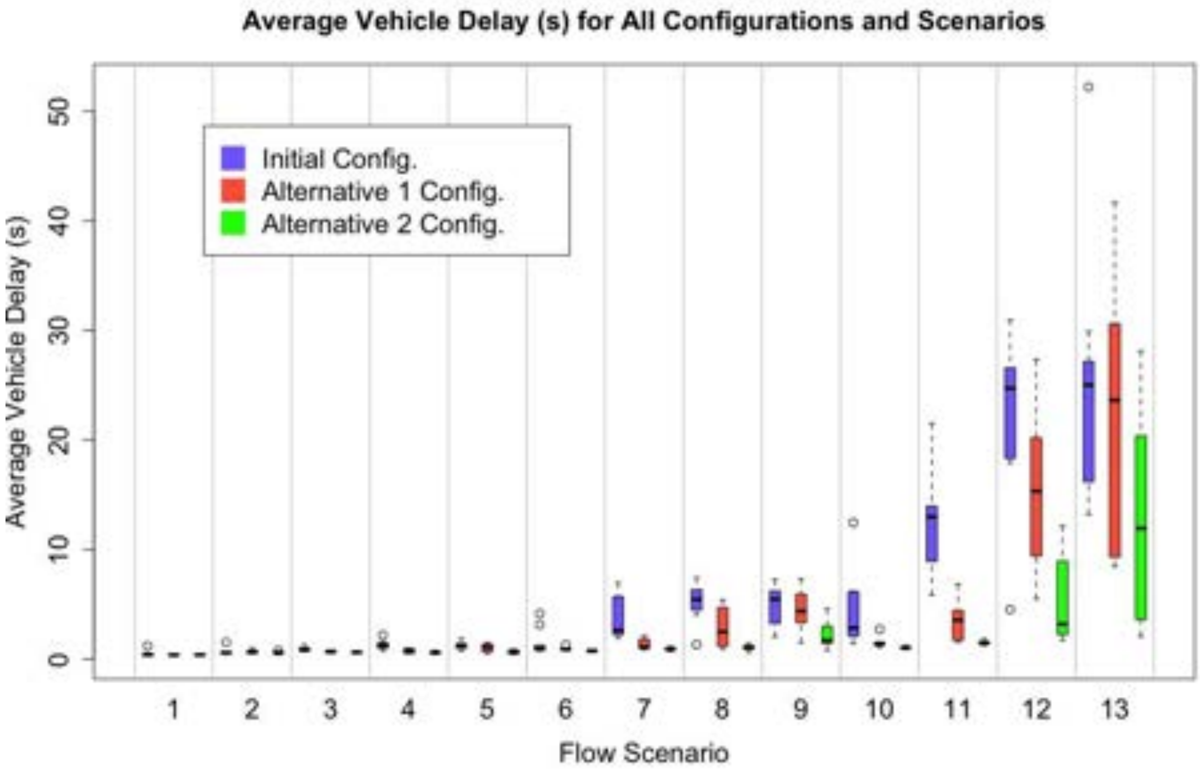
6.5. VISSIM Modeling Results

In this section, the main results from the study are presented in detail. Four main metrics were used to evaluate the performance of each curb configuration, addressing different aspects of how the curb design behaved under different flow and PUDO share conditions. In particular, the study focused on vehicle delay, occupancy rate, the number of vehicles parking, and the share of parking requests declined. Vehicle delay "is obtained by subtracting the theoretical (ideal) travel time from the actual travel time. Negative delay cannot occur [...] and the actual travel time does not include [...] parking time in real parking lots." [23]. The occupancy rate is the percentage of time that the parking spaces were occupied by parked vehicles during the data collection period. The number of vehicles parked distinguishes between vehicles parked at the curbside parking lot and vehicles double-parking. The share of parking requests declined is the number of vehicles that, while approaching the curb with the intention of parking, were not able to find an open space, saw their parking request declined and had to drive on. Only long-term parking vehicles were allowed this behavior, so the share of parking requests declined is a direct measure of how the curb is serving long-term parking vehicles. PUDO vehicles unable to park were instead diffused.

VISSIM output are presented as boxplots with each representing the distribution of the 10 runs for each scenario. For Alternative 1 and 2, two distinct curb configurations were examined. This was done to verify that the precise position of the PUDO zones did not have a significant influence on the results (as long as all the assumptions described were in place). Since for all the performance measures analyzed no significant difference was noted between the configuration setups, in this section only the results for Alternative 1 and 2 with PUDO zones at the ends are shown and compared to the base scenario. Further graphs containing the results for the other curb setups can be found in Appendix D.

6.5.1. Delay Results

The average vehicle delay was greatly influenced by the amount of time that the right-most lane was occupied by a double-parking vehicle. In most instances, the majority of the queue formed behind the double-parking vehicle (or the first of the double-parking vehicles, should more than one be present), and increased more rapidly the higher the flow of through traffic.



SCENARIO (PUDO %)

FIGURE 6-14. AVERAGE VEHICLE DELAY FOR ALL SCENARIOS AND ALL CONFIGURATIONS

Figure 6-14 shows both how the delay evolved between scenarios (from scenario 0 to scenario 3 (90% PUDO)) and between different curb configurations. Minimal to no delay was observed across Scenario 1 (low traffic flow) regardless of PUDO % or alternatives. At higher traffic volumes (Scenarios 2 and 3), minor delays were observed. Though a significant increase in delay was observed between scenarios (from negligible average delay to an average of 24 seconds of delay), the deployment of curb management strategies was effective in reducing average vehicle delay in most scenarios.

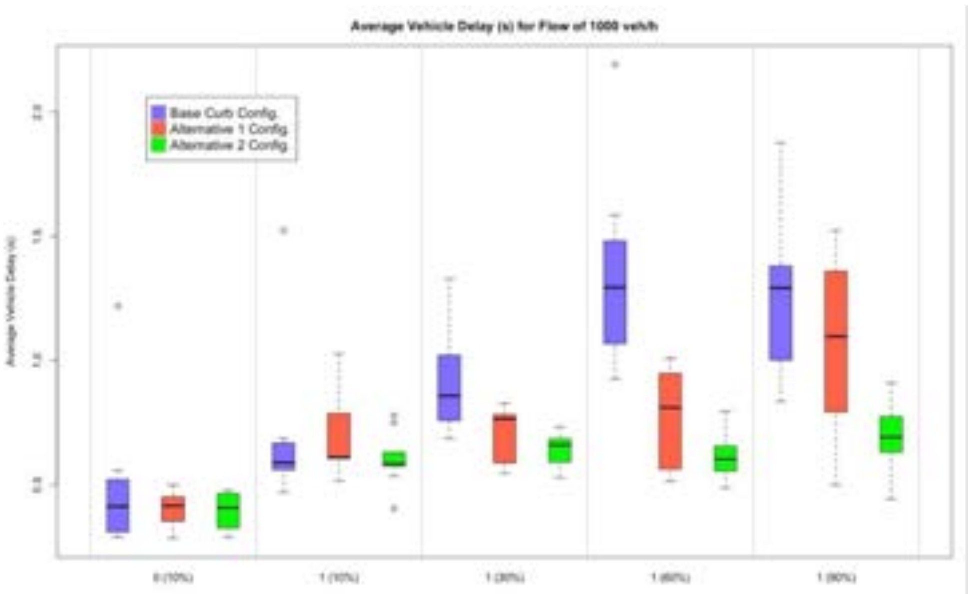
Table 6-4 synthesizes these changes, showing how even the introduction of just few dedicated PUDO spaces in Alternative 1, if done correctly so as to have a high compliance/utilization rate, can have a significant impact on the performance of the curb in almost all flow and PUDO % situations.

TABLE 6-4. PERCENT CHANGE IN AVERAGE VEHICLE DELAY - ALL SCENARIOS AND ALL CONFIGURATIONS

	Percent change in average vehicle delay												
Scenario	Base	Low Flow				Mid Flow				High Flow			
PUDO %	10%	10%	30%	60%	90%	10%	30%	60%	90%	10%	30%	60%	90%
Initial to Alt 1	-47%	-22%	-61% (**)	-67% (**)	-38%	-57%	-75% (**)	-48% (*)	-10%	-74% (*)	-75% (***)	-29% (-)	-10%
Initial to Alt 2	-50%	-36%	-68% (**)	-83% (***)	-76% (***)	-68% (-)	-87% (**)	-88% (***)	-64% (***)	-83% (*)	-92% (***)	-79% (***)	-51% (*)
Alt 1 to Alt 2	-6%	-18%	-19%	-48% (-)	-62% (*)	-27% (**)	-47% (*)	-78% (**)	-60% (**)	-35% (*)	-69% (**)	-71% (***)	-45% (-)

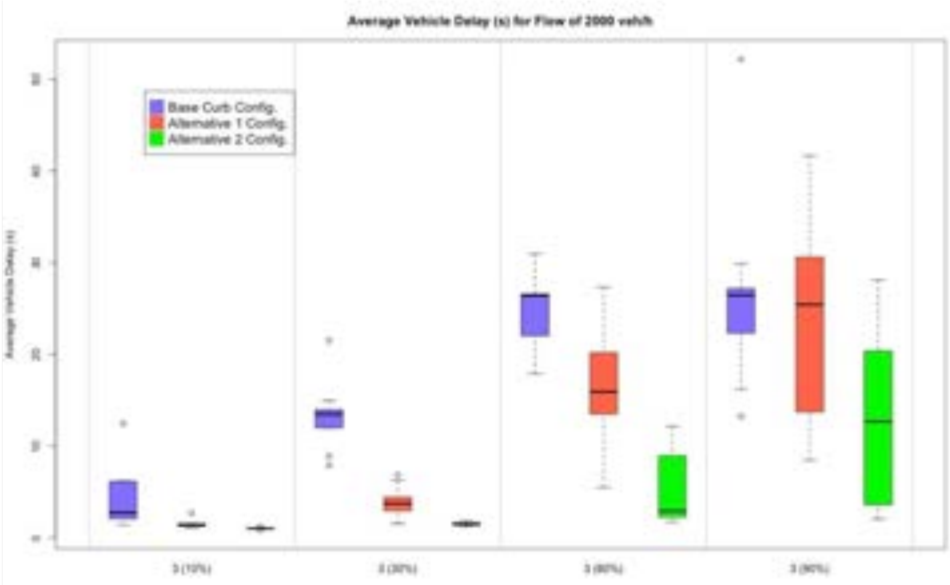
Welch Two Sample t-test, 95% Confidence Level: (-) = p-value < 0.1; (*) = p-value < 0.05; (**) = p-value < 0.01; (***) = p-value <0.001

Though a significant reduction in average vehicle delay was observed between the Base configuration and Alternative 1 configuration, an increase in the size of the PUDO zones (Alternative 2) improved the curb performance significantly for most scenarios (the greatest improvements were observed for scenarios 2 and 3, with percent reductions reaching above 70% in some cases). Though these results may be outsized compared to what would be observed in the field should these PUDO zones be implemented, due to the 100% attractiveness assumption already described, these results show the potential of this curb management strategy in reducing overall vehicle delay.



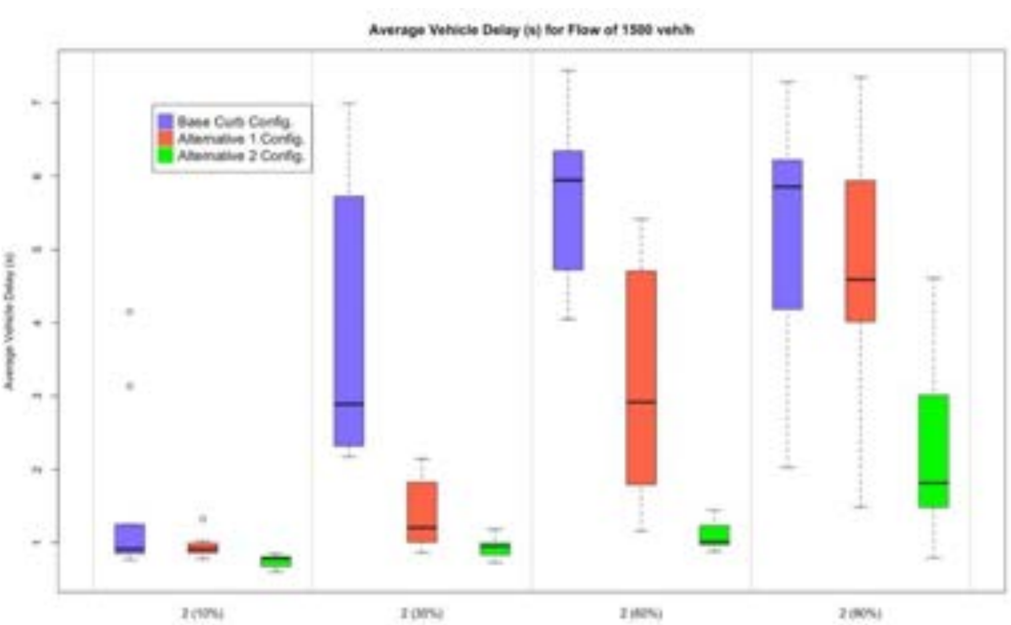
SCENARIO (PUDO %)

(a)



SCENARIO (PUDO %)

(b)



SCENARIO (PUDO %)

(c)

FIGURE 6-15. AVERAGE VEHICLE DELAY FOR 1000 VEH/H FLOW (A), 1500 VEH/H FLOW (B), AND 2000 VEH/H FLOW (C)

Figure 6-15 shows the detailed box plots for all the scenarios. Figure 6-15a represents the performance of the different curb configurations for low traffic flow (and relatively low parking demand). The minimal gains in performance are tied to the already minimal delay that characterized this set of scenarios. In Figure 6-15b there are significant gains shown for Alternative 1 in the mid-range PUDO share scenarios, while in Figure 6-15c significant reductions in delay are present when adopting Alternative 2 in all PUDO share scenarios.

6.5.2. Occupancy Rate

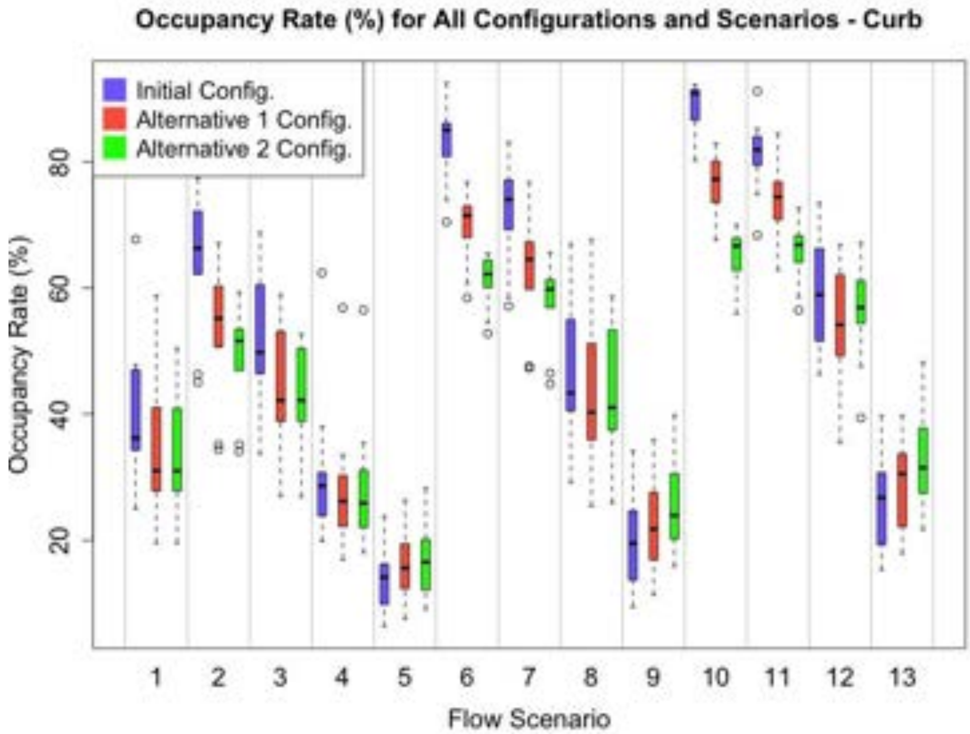
For each curb configurations, the average occupancy rate was examined by splitting the available parking spaces (which remained unchanged throughout the simulations) into two groups: curbside parking spaces, and double-parking spaces. Figure 6-16 shows a comprehensive comparison for both curb and double parking across all scenarios and curb configurations. As a general tendency, as the share (and number of) PUDO vehicles increased, the occupancy at the curb decreased. This is not surprising, as there is a sum of two effects occurring:

1. PUDO vehicles tend to stop for a shorter amount of time (their average dwell time is lower than that of long-term parking vehicles), thus physically occupying curb parking spaces for less time,
2. with an increase in PUDO vehicles, a higher number of parking events occurs in the right-most lane (double parking), as the percentage of double-parking vehicles is fixed at 40%

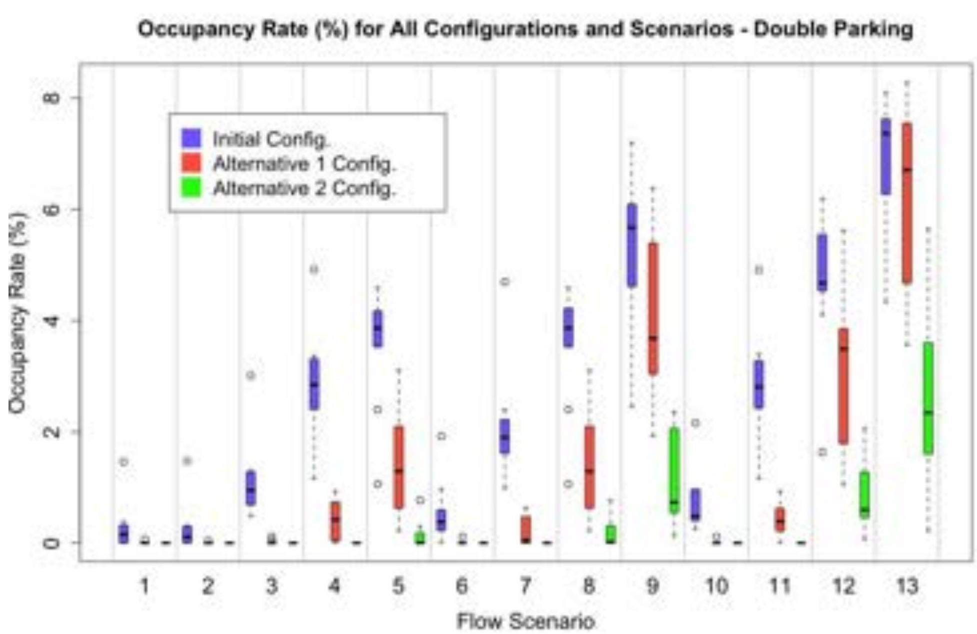
The main difference observed in Figure 6-16b between the different alternative configurations is that a significant proportion of PUDO vehicles are redirected to the designated PUDO zones instead of either parking in the general curb parking spaces or double-parking. This has two separate, but connected, effects:

1. it reduces the occupancy rate (and the number of vehicles parking) in the right-most lane, and
2. it slightly increases the occupancy rate of the curbside parking spaces at the curb (which take into consideration both the general parking spaces and the PUDO zones)

Globally, between the Base configuration and Alternative 2 configuration, the changes in occupancy rate between scenarios with the same flow characteristics (1000, 1500, and 2000 veh/h) are reduced, leading to a more uniform use of the curb even under drastically different PUDO share situations. This points to a more flexible curb setup (Alternative 2) which is able to handle varying curb demands



(a)



(b)

FIGURE 6-16. OCCUPANCY RATE FOR ALL FLOWS AND ALL CONFIGURATIONS. CURB PARKING (A) AND DOUBLE PARKING (B)

The changes described above are supported by the analysis of the average vehicle delay across curb configurations shown in Table 6-5. While there is a reduction in occupancy rate across all scenarios for double parking vehicles between the Base configuration and Alternatives 1 and 2, there is a stable increase in occupancy of the curb for high PUDO share (90%).

TABLE 6-5. PERCENT CHANGE IN OCCUPANCY RATE

(a) Curb parking

	Percent change in occupancy rate - curb												
Scenario	Base	Low Flow				Mid Flow				High Flow			
PUDO %	10%	10%	30%	60%	90%	10%	30%	60%	90%	10%	30%	60%	90%
Base to Alt 1	-16%	-18%	-15%	-9%	17%	-16%	-13%	-8%	13%	-14%	-9%	-8%	12%
Base to Alt 2	-18%	-24%	-18%	-8%	23%	-26%	-20%	-7%	27%	-27%	-19%	-5%	27%
Alt 1 to Alt 2	-2%	-8%	-4%	2%	6%	-12%	-8%	0%	13%	-14%	-11%	4%	13%

(b) Double-parking

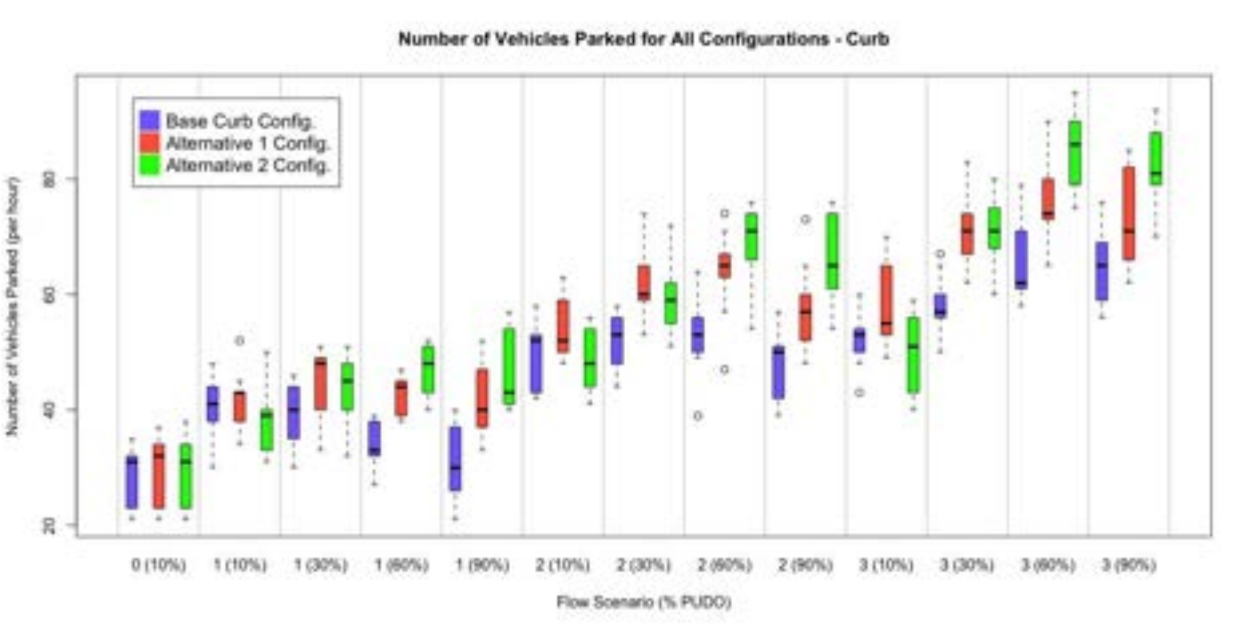
	Percent change in occupancy rate - double parking												
Scenario	Base	Low Flow				Mid Flow				High Flow			
PUDO %	10%	10%	30%	60%	90%	10%	30%	60%	90%	10%	30%	60%	90%
Base to Alt 1	-98%	-98%	-99%	-84%	-61%	-98%	-90%	-60%	-27%	-98%	-85%	-34%	-12%
Base to Alt 2	-100%	-100%	-100%	-100%	-96%	-100%	-100%	-96%	-80%	-100%	-100%	-82%	-64%
Alt 1 to Alt 2	-100%	-100%	-100%	-100%	-91%	-100%	-100%	-89%	-73%	-100%	-100%	-73%	-59%

6.5.3. Number of Vehicles Parked

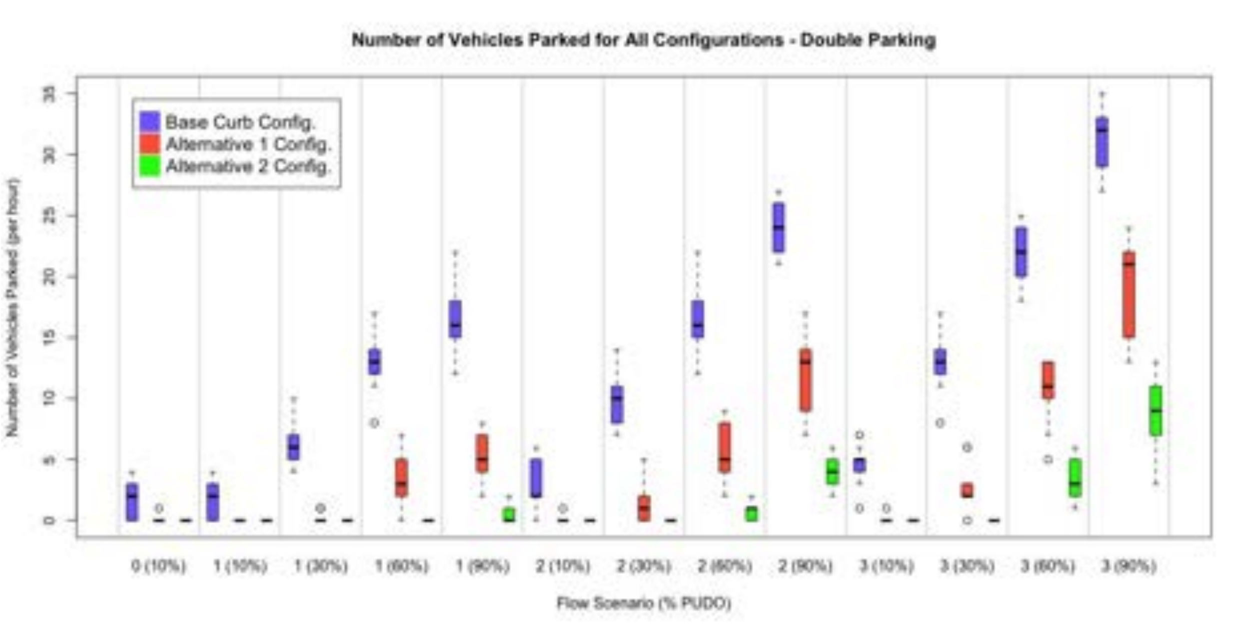
A slightly different perspective on curb productivity, though directly correlated to the occupancy rate, is given by the analysis of the number of vehicles parked. Given that, except for scenario 0, the overall parking rate is fixed at 5%, on average there are:

- for Scenario 0, 32 vehicles per hour attempting to park, with 4 PUDO
- for Scenario 1, 50 vehicles per hour attempting to park, with 5, 15, 30, and 45 PUDO for the 10%, 30%, 60%, and 90% scenarios respectively
- for Scenario 2, 75 vehicles per hour attempting to park, with 7.5, 22.5, 45, and 67.5 PUDO for the 10%, 30%, 60%, and 90% scenarios respectively
- for Scenario 3, 100 vehicles per hour attempting to park, with 10, 30,60, and 90 PUDO for the 10%, 30%, 60%, and 90% scenarios respectively

Due to the stochasticity of each simulation run, the exact parking demand and PUDO share of each run differed from the set average, which was however met by taking the mean demand and PUDO share across all 10 runs. Figure 6-17. a clearly shows greater curb productivity in the alternative configurations, and especially so for high flow and high PUDO shares.



(a)



(b)

FIGURE 6-17. NUMBER OF VEHICLES PARKED FOR ALL SCENARIOS AND ALL CONFIGURATIONS FOR CURB (A) AND DOUBLE-PARKING (B).

In addition to improving the productivity of the curb space, PUDO zones greatly reduces the amount of double parking that occurs, as demonstrated in Figure 6-17b. This conclusion is partially a result from the modeling assumption that PUDO vehicles would use a PUDO space if available. By relaxing this assumption, the results in Figure 6-17b would still hold, though to a lesser degree (especially if the zones are poorly designed and placed, or if they are not properly enforced).

6.5.4. Share of Parking Requests Declined

This metric constitutes the final piece of information necessary to understand the performance of the various curb configurations. Due to the nature of the models created in VISSIM, the only vehicles whose parking request could be declined are the “long-term” parking vehicles (i.e., the only vehicle category which was allowed to "drive on" in case no parking space was available). This means that the share of parking requests declined is an indicator of the curb's performance in dealing with the needs of long-term (or more traditional) parking behavior. In general, the capacity of the parking facility modeled in VISSIM was estimated to be between 50 and 75 vehicles per hour, depending on PUDO share and the randomness of the vehicle dwell times. This means that Scenario 3’s operations were being carried out in conditions where demand exceeded capacity. This is reflected in Figure 6-18, which shows how for low PUDO share the percentage of parking requests declined exceeded 40% in some cases.

Although the share of parking requests declined increased overall for most scenarios between the base configuration and alternative configuration 2 for low PUDO share runs, this loss in performance subsided for simulations with high PUDO shares. Though this is to be expected, as Alternative 2 removes almost 30% of the curb parking spaces from the availability of long-term parking vehicles, this loss in curb performance is:

- limited to specific demand characteristics (high share long-term parking requests),
- less-than-proportional to the loss in curb parking for long-term use, and
- countertrend to what is observed in alternative configuration 1.

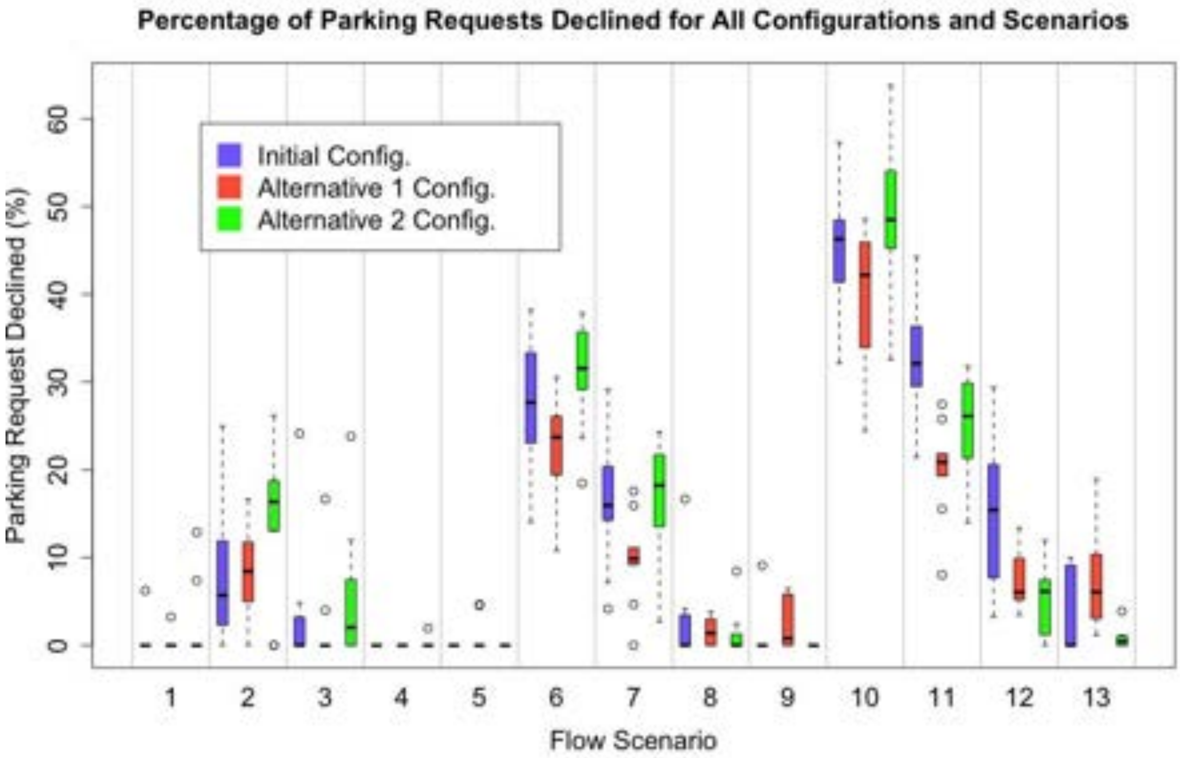
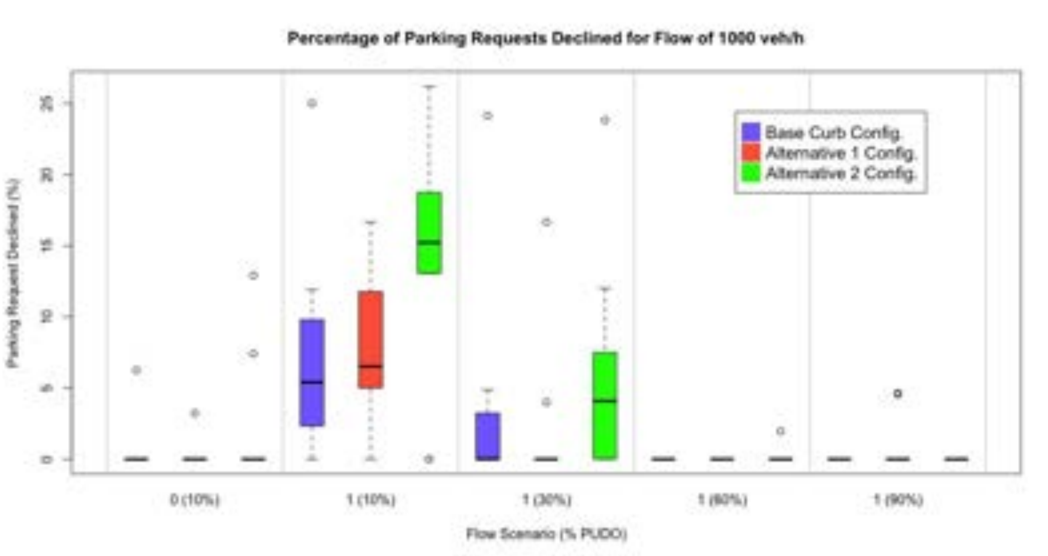
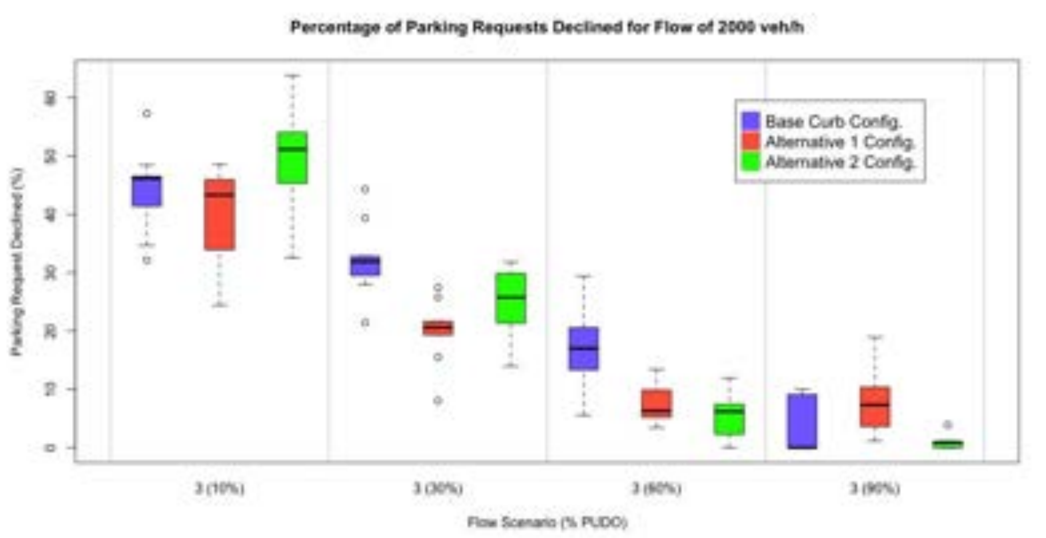


FIGURE 6-18. PERCENTAGE OF PARKING REQUESTS DECLINED (LONG-TERM PARKING VEHICLES)

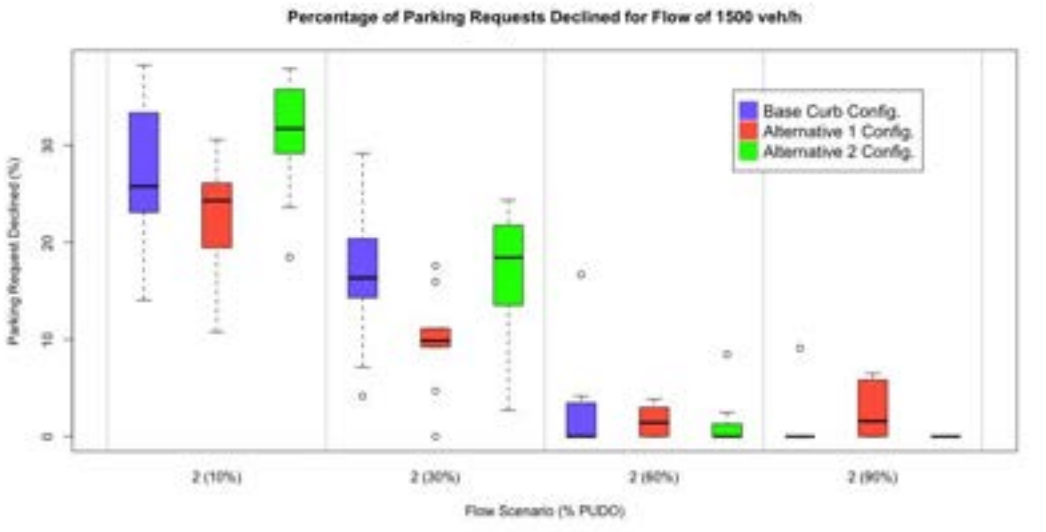
This final point can be observed in Figure 6-19.b and Figure 6-19.c, in which it can be seen that, specifically for low PUDO shares, the best performing configuration in terms of percentage of parking requests declined is Alternative 1. This result supports the idea that separating curb uses could lead to a better performance of the curb not only in terms of delay, but also in terms of fruition of the curb space for long-term (and short term) parking vehicles.


Percentage of Parking Requests Declined for Flow of 1000 veh/h
Base Curb Config.
Alternative 1 Config.
Alternative 2 Config.
Parking Request Declined (%)
0 (10%)
1 (10%)
1 (30%)
1 (60%)
1 (90%)
Flow Scenario (% PUDO)

(a)


Percentage of Parking Requests Declined for Flow of 2000 veh/h
Base Curb Config.
Alternative 1 Config.
Alternative 2 Config.
Parking Request Declined (%)
3 (10%)
3 (30%)
3 (60%)
3 (90%)
Flow Scenario (% PUDO)

(b)



(c)

FIGURE 6-19. PERCENTAGE OF PARKING REQUESTS DECLINED FOR FLOWS OF 1000 VEH/H (A), 1500 VEH/H (B), 2000 VEH/H (C)

6.5.5. Unprocessed and Diffused Vehicles

The final measurements collected and analyzed throughout the simulations were the number of unprocessed and diffused vehicles. Though only a limited number of simulation runs (and scenarios) were affected by unprocessed vehicles (as shown in Figure 6-20), this means that when evaluating the other results (specifically for scenario 3) this must be taken into consideration. The presence of unprocessed vehicles affected to some minor extent the measured delay (as additional queued vehicles accumulated outside the network) and the number of vehicles parked (as some vehicles looking to park never made it into the network), along with the occupancy rate and the share of parking requests declined.

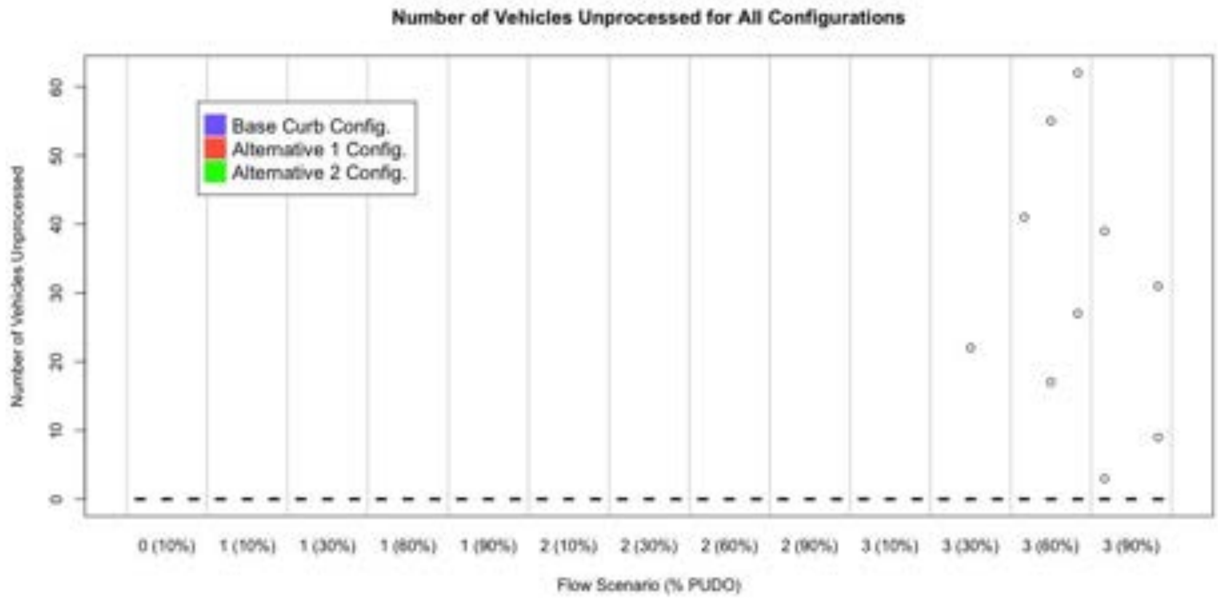


FIGURE 6-20. NUMBER OF UNPROCESSED VEHICLES FOR ALL CONFIGURATIONS AND ALL SCENARIOS

As for the number of diffused vehicles, Figure 6-21 shows how at most, on average, 7.8% of PUDO vehicles (the only vehicle class that would diffuse) diffused. No single curb configuration was immune to vehicles diffusing, with Alternative configuration 2 having vehicles diffused only for very high PUDO shares. Operating near or beyond the curb parking's capacity played an outsized role in causing vehicles to diffuse. This is supported by the observation that scenario 1 (and 0) simulations were the only scenarios largely free of diffused vehicles.

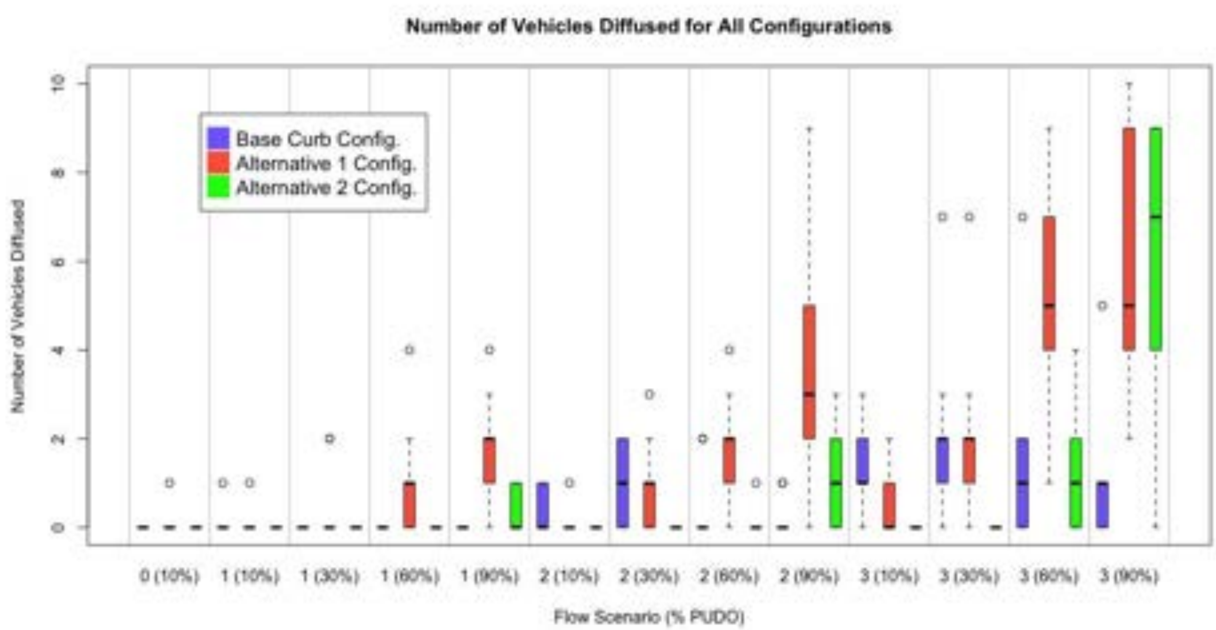


FIGURE 6-21. NUMBER OF DIFFUSED VEHICLES FOR ALL CONFIGURATIONS AND ALL SCENARIOS

6.6. Conclusions and Recommendations

Through data collection and calibrated microscopic simulation modeling, this study investigates the potential impacts of increased pick-up and drop-off activities in different flow and curb configurations. The data collection phase showed that the double-parking behavior is complex, and that a wider study would be required to model it in detail. Through the collection of curbside data, different parking behaviors were identified, and a quantitative distinction between pick-up/drop-off and long-term parking was observed. Analysis of simulation results indicate potential benefits with the introduction of curb management strategies. Should future transportation trends lead to an increase in the share of pick-up/drop-off activity at the curb, strategies which involve the separation of curb uses appear to be effective in reducing delay for vehicles and optimizing curb utilization. Throughout the simulations, a progressive shift away from traditional long-term parking towards PUDO led to an observed higher curb productivity and lower occupancy, although higher rates of double parking were recorded. The use of dedicated PUDO zones helps to reduce the likelihood of double parking and the associated delays. Additional field data collection and simulation analysis will be required to develop specific guidance for the number of PUDO dedicated spaces relative to overall traffic and parking demand. However, it is clear for this effort that such management has significant potential to improve overall curb utilization and performance.

The current effort does have several limitations that have been discussed, including a fixed rate for PUDO double parking, assumed 100% compliance with the use of PUDO zones, and vehicle diffusion and unprocessed vehicles. The use of a predefined diffusion time for vehicles waiting for a parking space is a necessary and imperfect modeling solution. With a better system in place, high-parking volume situations, in which many vehicles wait for parking to become available, can be explored. Nevertheless, despite these limitations, the use of microscopic simulation software was a good tool to explore and examine the impacts of different curb configurations on traffic flow and curb performance. Additional data collection capturing additional areas and conditions (e.g., the presence of PUDO zones) will allow for improved model calibration, resulting in even more robust simulations.

Future researchers should work to gather more curb and double-parking data in order to appropriately examine the potential impact of curbside parking availability and parking purpose (PUDOs, deliveries, etc.) on double-parking behavior. In addition, the effect of the placement of the PUDO zone (e.g., at the end of general parking, mixed within general parking, etc.) should be considered. As this study assumes compliance of PUDO vehicles, the topic of parking and double-parking enforcement should be further explored. The evaluation of safety impacts in different PUDO scenarios was also beyond the scope of the present study and should be examined in future research. In particular, the impact on weaving maneuvers and conflict areas of the proposed curb management strategies should be examined in greater detail. Additionally, future research efforts should explore modeling scenarios in which an increase in PUDO demand is not linked to a proportional decrease in long-term parking, but represents additional curb parking demand generated by users switching from other forms of transportation (transit, biking, walking, etc.) to ride-hailing services. Finally, as other curb space allocation strategies are proposed, a comprehensive modeling comparative study should be devised.

7.0. CONCLUSIONS AND RECCOMENDATIONS

The COVID-19 pandemic dramatically impacted modal preferences. As people were less willing to use modes where they encountered strangers (i.e. public transit and shared ride-hailing) and where they came into contact with shared surfaces (i.e. ride-hailing), it became crucial to understand the immediate and long-lasting effects of COVID-19 on shared mobility. Insights into transportation attitudes and behaviors during and after the pandemic should be used to inform transportation policies and reactionary safety measures. Lessons learned from this major disruption can be applied to other large events that impact the perception of risk in shared modes. Beyond the COVID-19 pandemic, understanding how disruption was perceived is especially important as cities work toward building resilient transportation systems.

During a disruptive event, online surveys can be a quick and cheap tool to deploy and capture attitudes and behaviors. Although online research surveys are ubiquitous and there are a variety of survey recruitment methods, sampling a targeted population can be difficult. When conducting online survey research, the sampling methodology is extremely important to the quality and representativeness of the sample; a balance must be struck between effort, time, and money versus the number and quality of survey responses. Surveying efforts should be described in detail with emphasis on the recruitment methodology. The recruitment method that collected the largest number of responses in this report at an affordable price was a paid panel service. Unfortunately, over half of the survey responses recruited through this method suffered from quality concerns and didn’t correctly pass the attentiveness check or contained gibberish. Reaching out to a panel of previous survey respondents (email recontact) proved to be the lowest effort and second most responsive recruitment method. Although the most expensive recruitment method was Facebook advertisements, other researchers have found success on the platform. The difference may be a result of the internal algorithm, specific targeting requirements, lack of monetary incentive, or visual stimulus. Mechanical Turk similarly has been used widely in academic research but was not successful in recruiting for this effort, likely due to the qualifier question. Reaching out to local community organizations with the request to circulate the survey required a high communication effort but resulted in a decent size sample of quality local respondents. No platform recruited evenly across the demographics and modal frequencies. In particular, community outreach and Facebook advertisements over-recruited females while community outreach and Qualtrics Panel over-recruited higher educated participants. Even when accounting for socio-demographics, the recruitment method impacted the analysis of attitudes, so it is important to acknowledge the recruitment method and limitations when interpreting the results. A mixed-recruitment sample that combines these methods can be utilized to provide a more complete dataset as long as the impact of the limitations in each recruitment method are understood.

Social distancing and stay-at-home orders at the start of the pandemic resulted in a significant decrease in the usage of shared mobility transportation modes. Potential virus exposure from other riders contributed to a lower level of comfort for shared modes throughout the pandemic. In response to this discomfort, shared modes implemented many precautionary measures and although these measures were generally viewed as positive and a portion of the population reported that they trusted these precautions, they did not result in a significant change in comfort. Respondents forecasted that the availability of a vaccine would increase their comfort using shared mobility but predicted it still would not completely return to pre-pandemic levels. Ordinal regression models and calculated marginal effects provide additional insight into the impact of demographics and other attitudes on shared mobility comfort during stages of the pandemic. Prior to the pandemic, higher income and older respondents were less likely to use shared ride-hailing. Extroversion and prior modal usage positively impacted respondents' attitude towards comfort in all shared modes. During the pandemic, these traditional factors (demographics and extroversion) were not as significant as other COVID-related factors that better explained the sample's general discomfort using shared rides. In response to questions pertaining to level of comfort in the future with a vaccine, male respondents were more likely to predict comfort with shared ride-hailing, which may be explained by differences in risk perception among genders. Linear regression models were used to explore the change in levels of comfort post-pandemic as a function of socio-demographic variables like race, income, and age. As the world returns to a "new normal" in which they will not fully return to previous comfort levels using shared mobility, this research provides essential insights for planners and policymakers to better prepare for the post-pandemic era.

To understand the lasting impact of the pandemic on attitudes, a Wave 2 online survey was distributed in October 2021, a year after the Wave 1 survey. A "new normal" phase was observed as some pre-COVID behaviors returned but the panel reported an increase in telecommuting and decreased usage of shared mobility. There was no significant change in usage or comfort during the COVID-19 Delta wave over the summer (between Summer 2021 and October 2021), so the spread of COVID-19 was not the only factor impacting the use of shared transportation modes. Although levels of comfort using shared modes have improved since the summer of 2021, participants reported that their comfort using transit, ride-hailing, and shared ride-hailing would still not fully return to pre-pandemic levels by October 2022. These conclusions may be limited as the majority of the panel was not a shared ride-hailing user and was older, more highly educated, majority white, higher income, and more vaccinated than the Atlanta population. Additional changes in panel attitudes occurred in statements related to comfort in shared mobility and masking. The presence of masks in shared environments improved comfort levels, especially in transit and a small, enclosed space. Analysis of estimated bivariate ordered probit models found that a "Vaxxed and/or Relaxed" attitude increased comfort in shared modes regardless of the presence of masks. Masks had a smaller magnitude of impact on comfort with shared ride-hailing, which indicates that factors beyond masks and proximity to other passengers influence comfort in the "new normal" era. Shared mobility agencies should investigate additional precautionary measures, other than encouraging masks, to increase the comfort of riders with a "Pandemic Mindset". Suggestions include shortening the length of shared rides by establishing modal priority or providing some information about the other riders. Transit agencies with a larger COVID-cautious population should consider continuing mask requirements. As the federal transit mask mandate expired in April 2022, future work can better capture the attitudes towards shared mobility without masks now that it is a real scenario. Respondents may have been overly optimistic regarding attitudes in a no-mask environment such as they were in when forecasting their attitudes once a vaccine was available. This study found that respondents were overly optimistic about their future level of comfort. This trend was especially significant for higher income individuals when predicting their transit comfort, indicating that these “choice riders” were the least accurate and were overly optimistic about using transit in the near future. The pandemic disrupted shared environment experiences and caused uncertainty regarding comfort in shared modes. As people gained experience and knowledge of the virus, their expectations of returning to pre-pandemic attitudes have lowered.

Findings from the panel survey were not fully exhausted and additional work could be developed with the existing data. Future efforts could include exploring how attitudes and demographics impact the second wave change in comfort, examining if the change in attitudes resulted in a behavior change, and understanding the impact of recruitment methodology on other attitudinal variables. The existing sample could be weighted to properly reflect the population composition with respect to key demographic variables to add richness to the conclusions. Due to the time frame of the study, actual usage of shared ride-hailing was not measured as shared ride-hailing services had not returned to the Atlanta area. As this service returns to the shared marketplace in cities across the globe, future studies should continue to investigate the usage and attitudes toward shared ride-hailing. Other contemporary studies have much larger sample sizes and additional data variables due to their longer survey tools. As this final report is being published before the findings of the larger research efforts, it serves an important role in understanding the longer-term impacts of the pandemic on attitudes. Additionally, this was the only survey effort solely focused on a city in the southeastern U.S. As the southeast eased COVID restrictions at a quicker pace than other coastal US cities, this study effort could inform other cities of future “new normal” attitudes.

While examining the different types of shared modes, complex relationships between size, shape, number of passengers, and level of comfort using shared vehicles emerged. Although the panel indicated that they would feel comfortable in small indoor spaces (i.e. elevator), they would not feel the same level of comfort in a shared ride-hail or transit vehicle. Proximity to a stranger was a major deterrent to many individuals embracing shared mobility, especially entering the “new normal” era, but other variables may impact willingness to share space. Shared autonomous vehicle engineers have the responsibility to design these new vehicles with these complex attitudes in mind. Further research should expand this idea to establish a safe and comfortable sharing environment suitable for the additional number of passengers.

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9.0 APPENDICES

Appendix A – Associated websites, data, etc., produced

Journal Articles:

Kiriazes, R., & Watkins, K. Impact and analysis of rider comfort in shared modes during the COVID-19 pandemic. *Transportation Research Part A: Policy and Practice*. Vol. 165, 2022, pp. 20-37.

Saracco, M., Kiriazes, R., Watkins, K., & Hunter, M. Carving Up the Curb: Evaluating Curb Management Strategies for Ride-Hailing and Ride Sharing Activity through Simulation. Presented at the 102nd Transportation Research Board Annual Meeting. Washington, D.C. , 2023.

Data Available:

Microscopic Simulation Analysis of Curb Environments: doi.org/10.5281/zenodo.7314646

Appendix B – Summary of Accomplishments

Date	Type of Accomplishment	Detailed Description
November 2019	Educational Product	Shorter Powerpoint presentation about Curbside Management created and presented in Engineering Communications course
September 2019	Educational Product	Powerpoint presentation about Curbside Management created and presented in undergraduate Multimodal Transportation course
January 2020	Student Award	STRIDE Student of the Year – Rebecca Kiriazes
March 2020	Conference Presentation	Submitted abstract for Conference on Sustainability and Emerging Transportation Technology (SETT).
June 2020	Student Award	Center for Transportation Equity, Decisions, and Dollars (CTEDD) Student Thesis/Dissertation Scholarship – Rebecca Kiriazes
September 2020	Educational Product	Developed Curbside management homework assignment for undergraduate Multimodal Transportation course
October 2020	Conference Presentation	Submitted abstract for presenting at Regional UTC Student Spotlight Virtual Conference for the Southeastern Region
December 2020	Publication	Submitted paper to Special Issue of TRB Part A (Policy and Practice): Characterizing Health Pandemic Impacts on Transportation Systems and the Demand for Mobility
December 2020	Conference Presentation	Submitted poster and presentation for Regional UTC Student Spotlight Virtual Conference for the Southeastern Region. The poster won 2nd Place in the 2021 STRIDE Poster Competition
May 2021	Student Award	Revolutionizing Engineering Departments (RED) Initiative Fellow – Rebecca Kiriazes
May 2021	Student Award	Georgia Tech CEE Future Faculty Fellow – Rebecca Kiriazes
March 2022	Conference Presentation	Podium presentation, "Perception of Shared Mobility Throughout the COVID-19 Pandemic" by Rebecca Kiriazes, for 7th Annual Regional UTC Conference for the Southeastern Region in Boca Raton, FL.
May 2022	Student Award	HDR Transportation Scholarship Program – Matteo Saracco
June 2022	Conference Presentation	Submitting paper to 2023 Transportation Research Board Annual Meeting on Curb Management Simulation.
July 2022	Student Accomplishment	Defense of Ph.D. Thesis "Understanding Attitudes and Behaviors Associated with Shared Mobility During Disruptive Events and Times of Uncertainty"– Rebecca Kiriazes

Appendix C – Additional Graphs and Figures

Chapter 3: Literature Review of Transportation Surveys During the Pandemic Table

Reference	Survey Topic	Key Findings	Location	Sample Size	Date of Data Collection	Survey Method	Recruitment Method (RM)	Mention of RM Impact
(Anke et al., 2021)	Mode-Choice	Shift away from public transport and increase in car, walk and cycle use.	Germany	4157	March 20 - May 15 2020	Web-based Survey	Social media, newsletters and mailing lists	X
(Fatmi et al., 2021)	Travel Activity Shopping	Higher income, younger and middle-aged, and full-time workers are more likely to decrease their out of home activity during COVID.	Kelowna region, Cananda	202	March 24 - May 9, 2020	Web-based Survey	Paid social media advertising	X
(Beck & Hensher, 2020a)	Activity participation Work from home (WFH)	Australians have limited travel and social contact.	Australia	1073	March 30 - April 15, 2020	Web-based Survey	PureProfile	
(König & Dreßler, 2021)	Mode-Choice Travel Activity Rural	A high share of respondents experienced no changes in their mobility behavior due to the pandemic but nearly one third of trips were also cancelled overall. A modal shift was observed towards the reduction of trips by car and bus, and an increase of trips by bike. The majority of respondents did not predict strong long-term effects on their mobility behavior.	Northern Germany	301	April and May 2020.	Telephone interview, paper survey, web-based survey	Randomly selected households in the study area by direct mail and social media platforms	X
(Politis et al., 2021)	Trip Frequencies	Decrease in trip frequencies due to the lockdown (significant correlations between gender and income during the lockdown).	Greece	1259	April 6-9, 2020	Web-based Survey	Online service using news nationwide outlets	X
(Kolarova et al., 2021)	Mode-Choice WFH	Increase in car use and decrease in public transport use as well as more negative perception of transit.	Germany	1000	April 6 -10, 2020	Web-based Survey	Paid panel provider (KANTAR GmbH)	X

CHAPTER 3: LITERATURE REVIEW OF TRANSPORTATION SURVEYS DURING THE PANDEMIC TABLE CONTINUED								
Reference	**Survey Topic**	**Key Findings**	**Location**	**Sample Size**	**Date of Data Collection**	**Survey Method**	**Recruitment Method (RM)**	**Mention of RM Impact**
(Shamshiripour et al., 2020)	Online Shopping WFH Perceived Risk	Transit and pooled ride-sharing services are associated with medium to extremely high exposure risks, resulting in the usage of safer alternatives. Working from home carries high potential in the future.	Chicago metro area, Illinois, USA	915	April 25, 2020, to June 2, 2020	Web-based Survey (Qualtrics)	Quotas through online panel survey company Qualtrics	
(Awad-Núñez et al., 2021)	Willingness to Pay Shared Mobility	Provision of covers for handlebars and steering wheels, increase of supply, and vehicle disinfection may result in a greater willingness to use public transport and sharing services post-COVID	Spain	984	April 28 - May 5, 2020	Web-based Survey	N/A	
(Das et al., 2021)	Mode-Switch Public Transport	Significant decline in public transport uses post-pandemic. Hygiene / cleanliness and travel time influence mode switch behavior. Large shift in commute from transit to cars as trip time increases.	India	840	April 29 - May 20, 2020	Web-based Survey	Social media, email, and professional networks	
(Ozbilen et al., 2021)	Risk Perception Mode Choice	Shared modes are “riskier” than cars (controlling for sociodemographic). Decreases in travel demand may resume after restrictions are lifted.	Columbus, Ohio, USA	436	April 30 to May 7, 2020	Web-based Survey (Qualtrics)	Qualtrics Panel	
(Watson-Brown et al., 2021)	Drunk Driving	Alcohol consumption and prior engagement in drunk driving were associated with drunk driving during COVID-19 restrictions.	Queensland, Australia	1193	April to mid-August 2020	Web-based Survey	Paid social media ads (Facebook Instagram)	X
(Anwari et al., 2021)	Mode-Choice WFH	COVID-19 caused large variation in mode preferences but small variation in trip frequencies. Males still go outside for work and shopping. Online work or education and shopping seems to be limited to urban areas.	Bangladesh	572	May 1 - 30, 2020	Web-based Survey	Social media (paid and convenience)	X

Chapter 3: Literature Review of Transportation Surveys During the Pandemic Table Continued								
Reference	**Survey Topic**	**Key Findings**	**Location**	**Sample Size**	**Date of Data Collection**	**Survey Method**	**Recruitment Method (RM)**	**Mention of RM Impact**
(Bohman et al., 2021)	Telework	Possibility to telework affects different groups differently in terms of gender, geography and mobility.	Malmö City, Sweden	636	May 8-27, 2020	Web-based Survey (Maptionnaire)	Established networks and social media (paid and convivence)	X
(Abdullah et al., 2021)	Mode-Choice Travel Activity	Significant shift in primary traveling purpose from work and studying to shopping during the pandemic. Significant modal shift from motorbike to non-motorized modes of travel was found for short distances and for longer distances, people shifted from transit to cars.	Lahore, Faisalabad, and Rawalpindi Pakistan, Punjab, Pakistan	671	May 09 to 31, 2020	Web-based Survey	Emails, social media websites and personal contacts	X
(Abdullah et al., 2020)	Mode-Choice	The majority of trips were made for shopping during the pandemic. There was a significant shift from public transport to private transport and non-motorized modes. Gender, car ownership, employment status, travel distance, the primary purpose of traveling, and pandemic-related were underlying factors.	Global	1203	May 9 - 31, 2020	Web-based Survey (Google forms)	Emails and social media channels (Facebook, LinkedIn, Reddit, and ResearchGate)	X
(Barbieri et al., 2021)	Perceived Risk	Substantial reductions in the frequency of all types of trips and use of all modes. Airplanes and buses are perceived to be the riskiest transport modes. Avoidance of transit is consistently found across the countries.	Australia, Brazil, China, Ghana, India, Iran, Italy, Norway, South Africa and the United States	9,394	May 11-31, 2020	Web-based Survey (Google forms)	Purposive and snowball techniques. (Direct emails and social media networks)	X
(Irawan et al., 2020)	Activity participation	Trips in new normal conditions are not completely replaced by the experience of virtual activities	Indonesia	834	Middle to the end of May 2020	Web-based Survey	N/A	X
(Yabe et al., 2021)	WFH Substitution	Internet use for socializing, exercise, and leisure/entertainment had a strong substitution with outings. Weak substitution relationship between Internet use for daily shopping and outings.	Japan	928	May 19 - 23, 2020	Web-based Survey	Quotas through online panel survey company Cross Marketing Inc	X

CHAPTER 3: LITERATURE REVIEW OF TRANSPORTATION SURVEYS DURING THE PANDEMIC TABLE CONTINUED								
Reference	**Survey Topic**	**Key Findings**	**Location**	**Sample Size**	**Date of Data Collection**	**Survey Method**	**Recruitment Method (RM)**	**Mention of RM Impact**
(Beck & Hensher, 2020b)	WFH	Aggregate travel, motor vehicle travel, concerns about public transport, and concern about the risk of COVID-19 will return to pre-COVID levels but not fully.	Australia	1073	May 23 - June 15, 2020	Web-based Survey (PureProfile)	Quotas through online panel survey company PureProfile	
(Ragland et al., 2020)	Travel Activity Mobility Patterns	COVID-19 pandemic and “shelter-in-place” order had a major impact on senior mobility.	Contra County, California	302	June 2020	Telephone interview and web-based survey	Recontact from 2018 survey, email and phone lists	X
(Ehsani et al., 2021)	Mode-Choice	Significant decreases were reported for public transit, personal vehicle use, and walking. No change in reported bicycle use. In the future, no significant difference in travel using personal vehicles, public transit, and walking compared to pre-pandemic levels.	USA	2,011	June 17 -29, 2020	Web-based Survey	Quotas through online panel survey company (Harris Paid Panel)	
(Cusack, 2021)	Active Transportation	Nearly half of respondents changed their commute mode during the pandemic. Significantly higher odds of active transportation among those who reported safety concerns around germs.	Philadelphia, PA, USA	213	June and August 2020	Web-based Survey (Qualtrics)	Targeted recruitment strategies	X
(Loa & Nurul Habib, 2021)	Ride-Sourcing Perception of Risk	COVID-19 has led to reduced demand and willingness to use ride-sourcing because of reductions in overall travel demand and increased perceptions of risk and concerns about shared surfaces.	Greater Toronto Area (GTA), Canada	920	July 2020	Web-based Survey	Random sample through a market research panel	
(Menon et al., 2020)	Mode-Choice Travel Activity	Public transit and ride-hailing ridership have greatly decreased during the lockdowns. Bike sharing operations have increased and have potential post-COVID-19.	USA	2,432	July-August 2020	Web-based Survey (Qualtrics)	Paid panel provider (Prime Panels)	X

CHAPTER 3: LITERATURE REVIEW OF TRANSPORTATION SURVEYS DURING THE PANDEMIC TABLE CONTINUED

Reference	Survey Topic	Key Findings	Location	Sample Size	Date of Data Collection	Survey Method	Recruitment Method (RM)	Mention of RM Impact
(Holte et al. 2020)	Perceived Risk	Males are less likely to change travel during COVID-19.	USA	2168		Web-based Survey	Random sample through GfK Group's KnowledgePanel	
(Guzman et al., 2021)	Activity participation	Low-income people are more socially exposed to contagion and have adverse economic and travel effects than other income groups.	Bogota, Columbia	776	N/A month 2020	Web-based Survey	Social media (e.g., Twitter, email, and web)	X

Chapter 6: Delay, Occupancy, Number of Vehicles Parked, and Number of Parking Request Figures

DELAY GRAPHS (ALL VEHICLES)

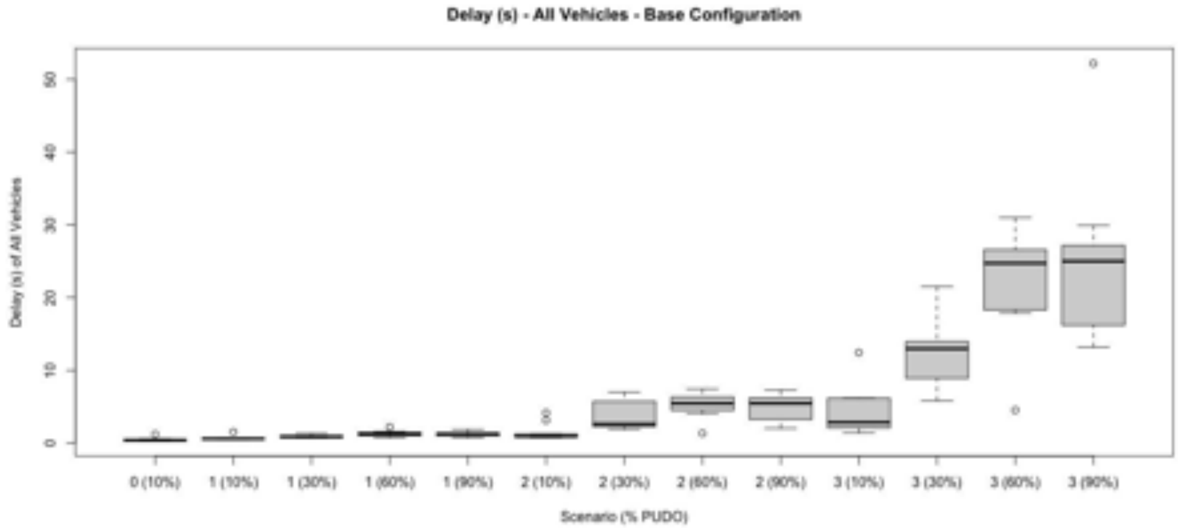

FIGURE 9-1. DELAY OF ALL VEHICLES ACROSS ALL SCENARIOS - BASE CONFIGURATION

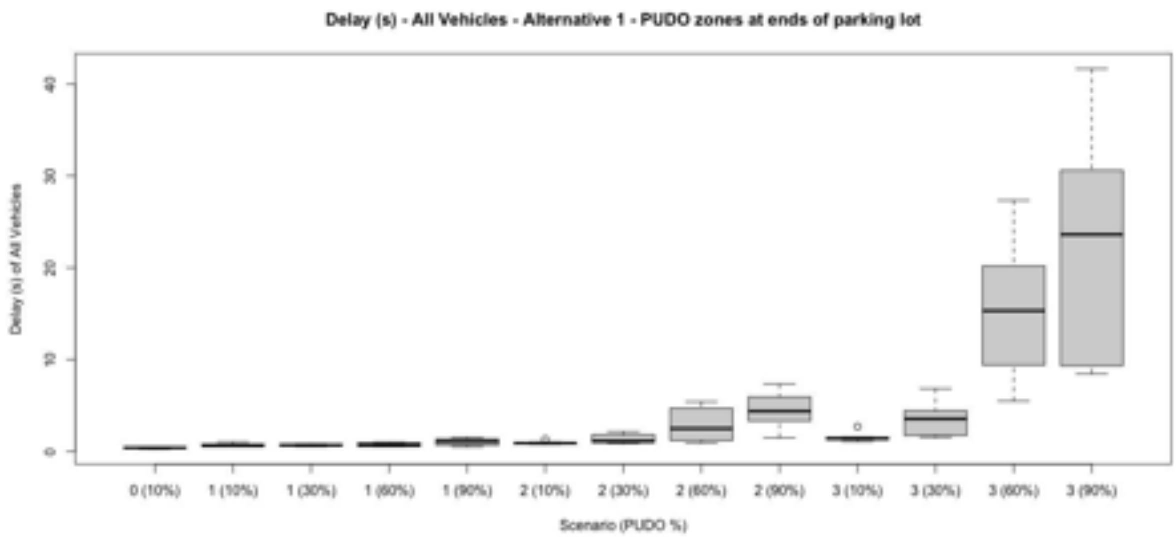

FIGURE 9-2. DELAY OF ALL VEHICLES ACROSS ALL SCENARIOS - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

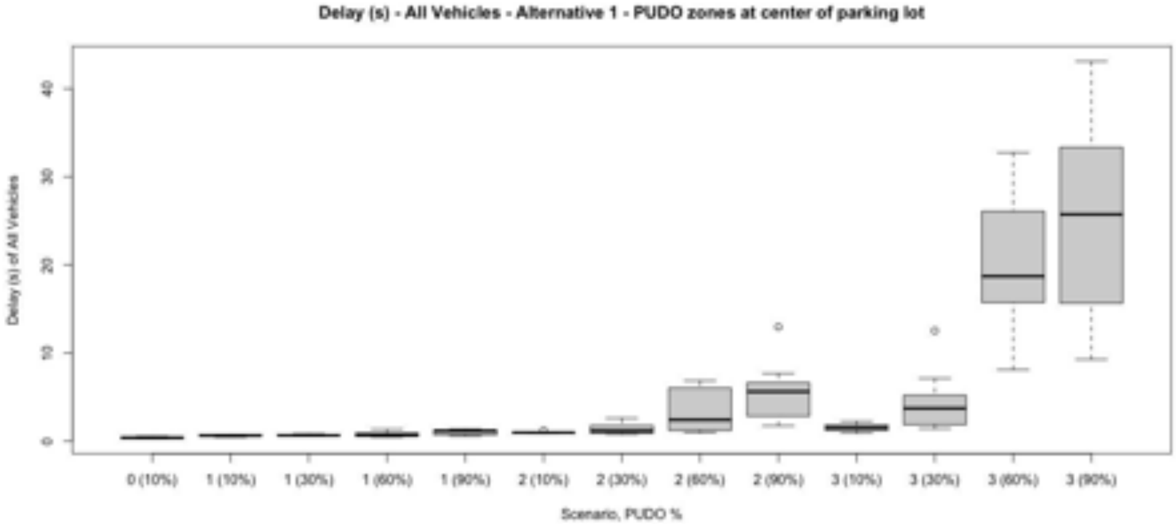

FIGURE 9-3. DELAY OF ALL VEHICLES ACROSS ALL SCENARIOS - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

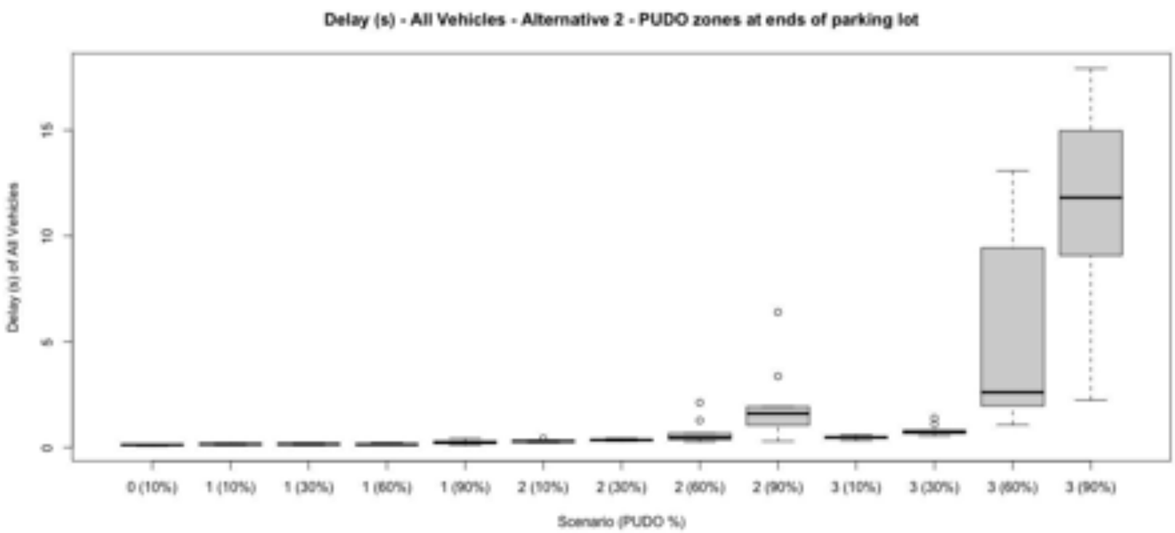

FIGURE 9-4. DELAY OF ALL VEHICLES ACROSS ALL SCENARIOS - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

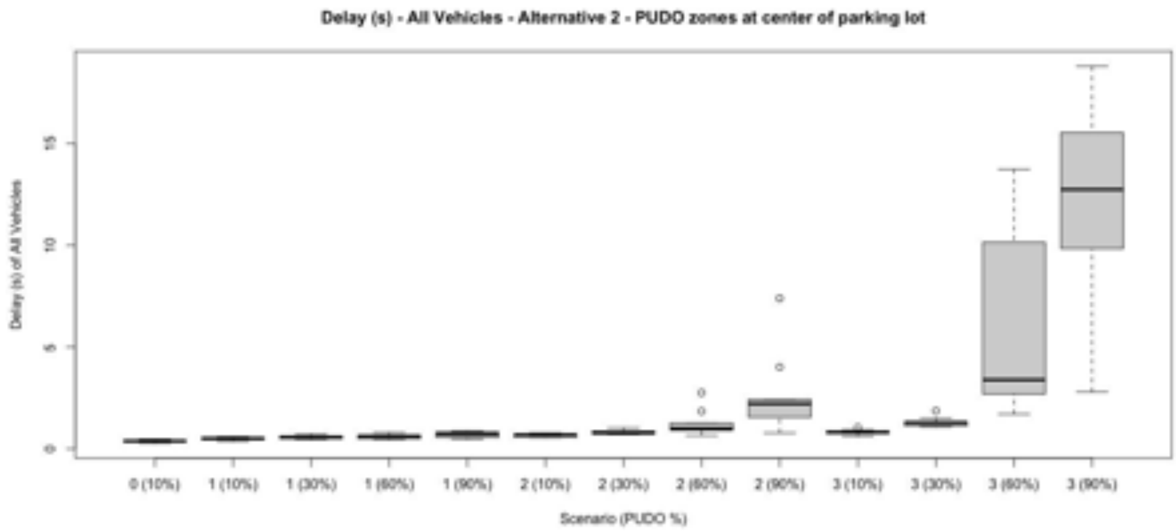

FIGURE 9-5. DELAY OF ALL VEHICLES ACROSS ALL SCENARIOS - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

DELAY GRAPHS (THROUGH VEHICLES)

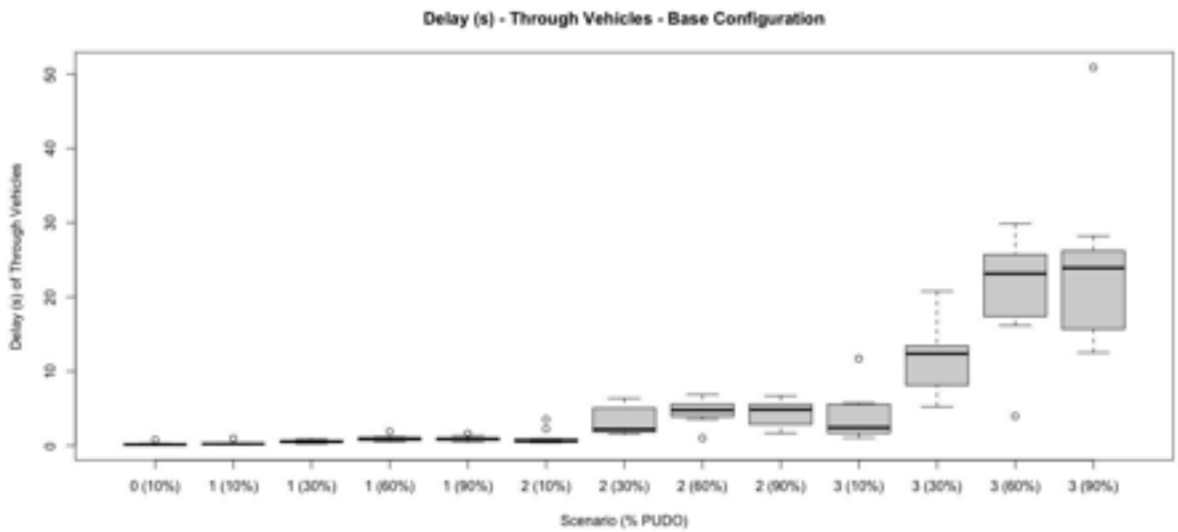

FIGURE 9-6. DELAY OF THROUGH VEHICLES ACROSS ALL SCENARIOS - BASE CONFIGURATION

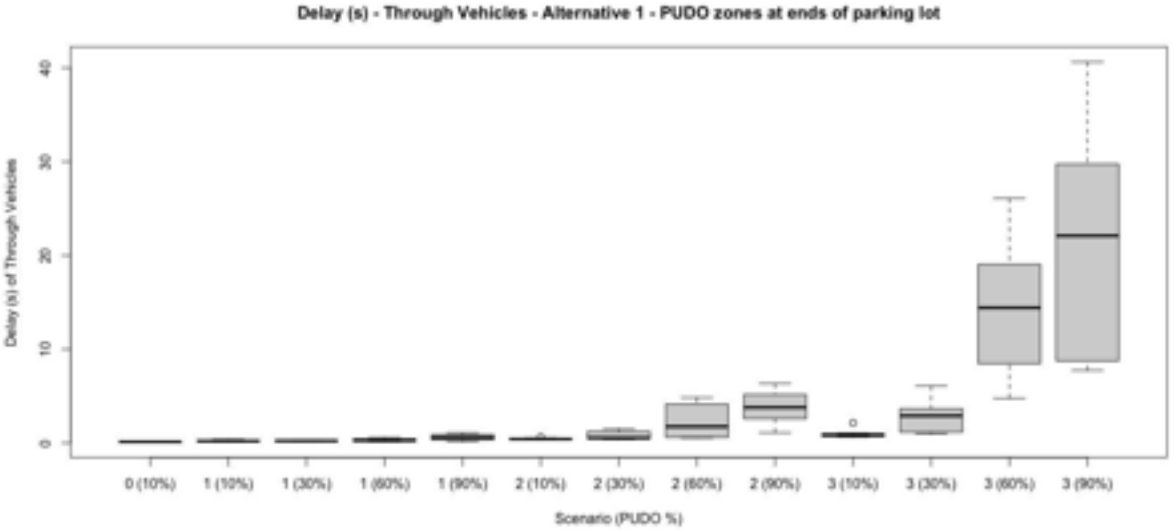

FIGURE 9-7. DELAY OF THROUGH VEHICLES ACROSS ALL SCENARIOS - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

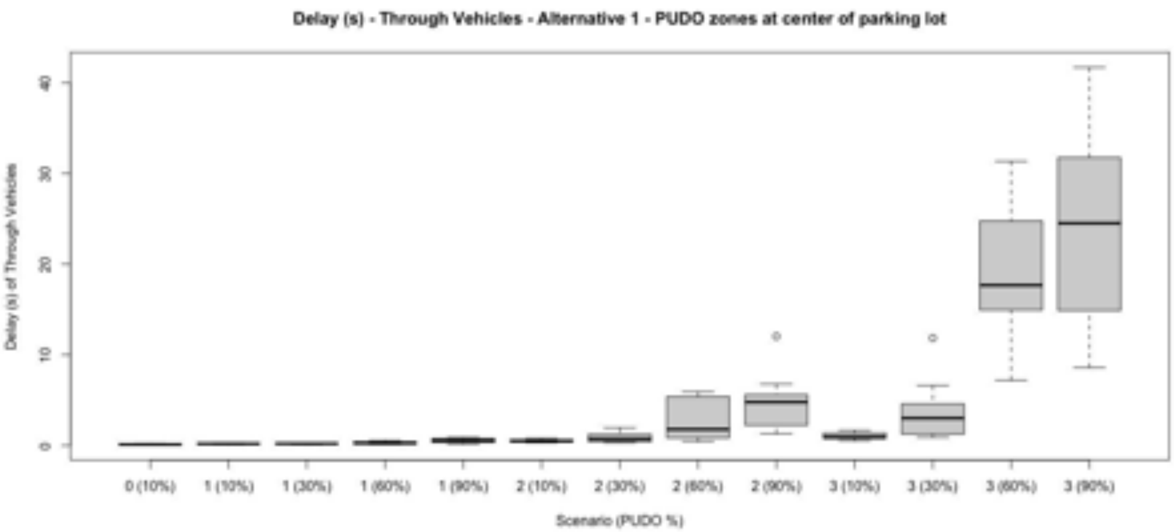

FIGURE 9-8. DELAY OF THROUGH VEHICLES ACROSS ALL SCENARIOS - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

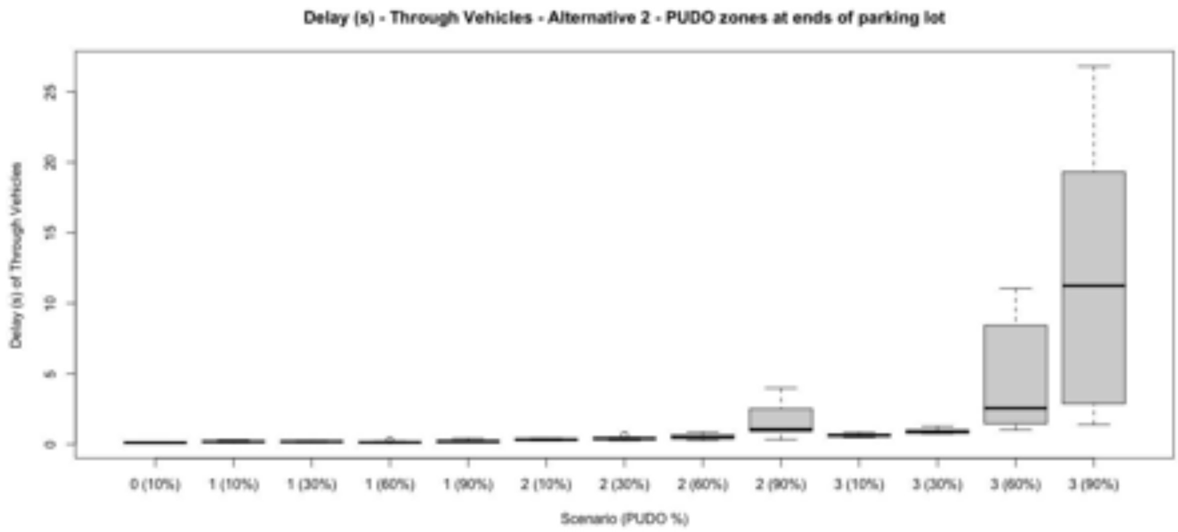

FIGURE 9-9. DELAY OF THROUGH VEHICLES ACROSS ALL SCENARIOS - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

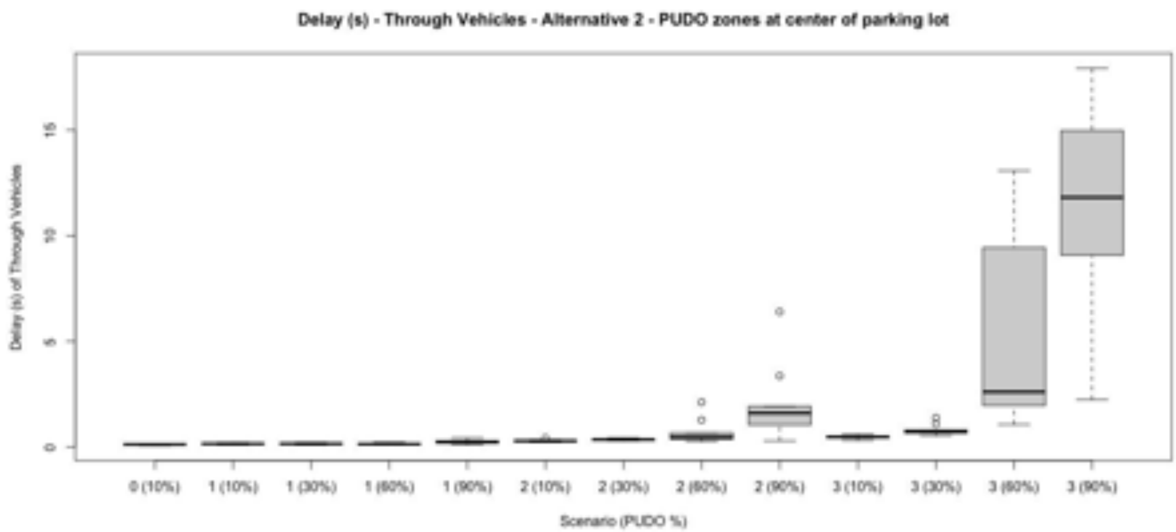

FIGURE 9-10. DELAY OF THROUGH VEHICLES ACROSS ALL SCENARIOS - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

OCCUPANCY RATE (CURB)

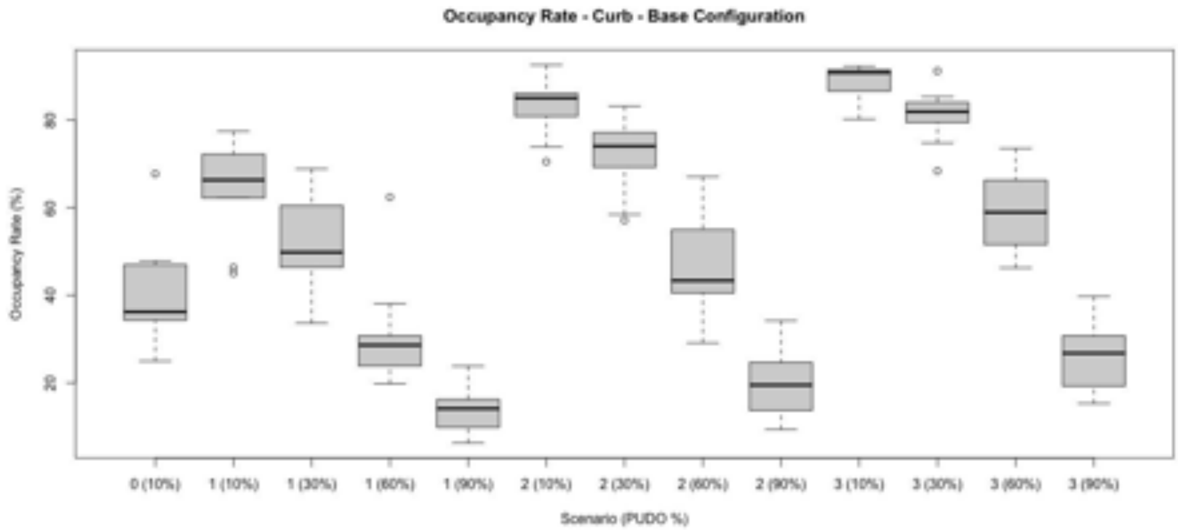

FIGURE 9-11. OCCUPANCY RATE AT THE CURB - BASE CONFIGURATION

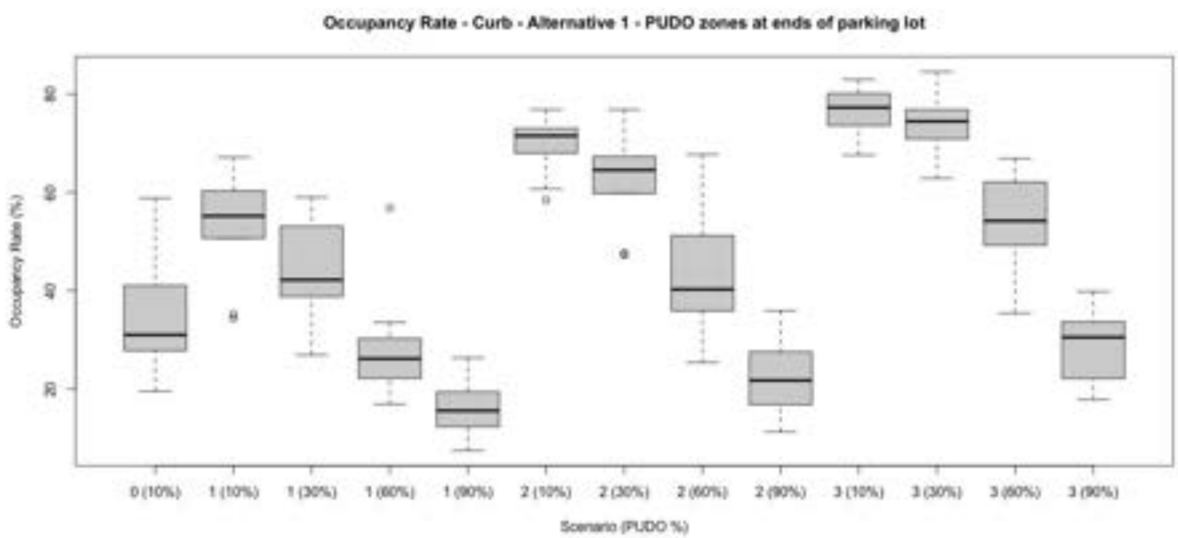

FIGURE 9-12. OCCUPANCY RATE AT THE CURB - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

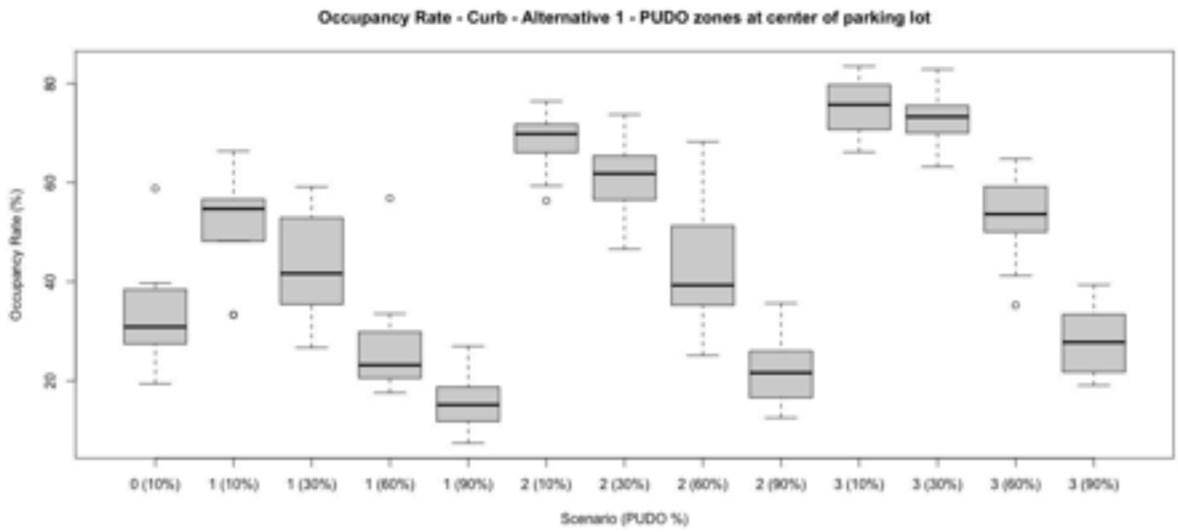

FIGURE 9-13. OCCUPANCY RATE AT THE CURB - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

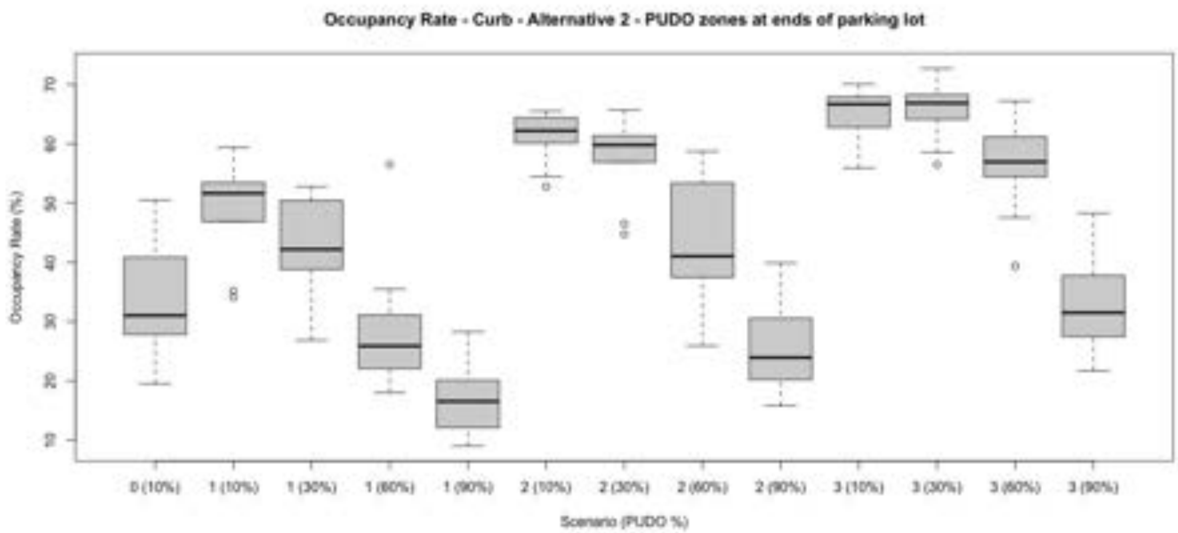

FIGURE 9-14. OCCUPANCY RATE AT THE CURB - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

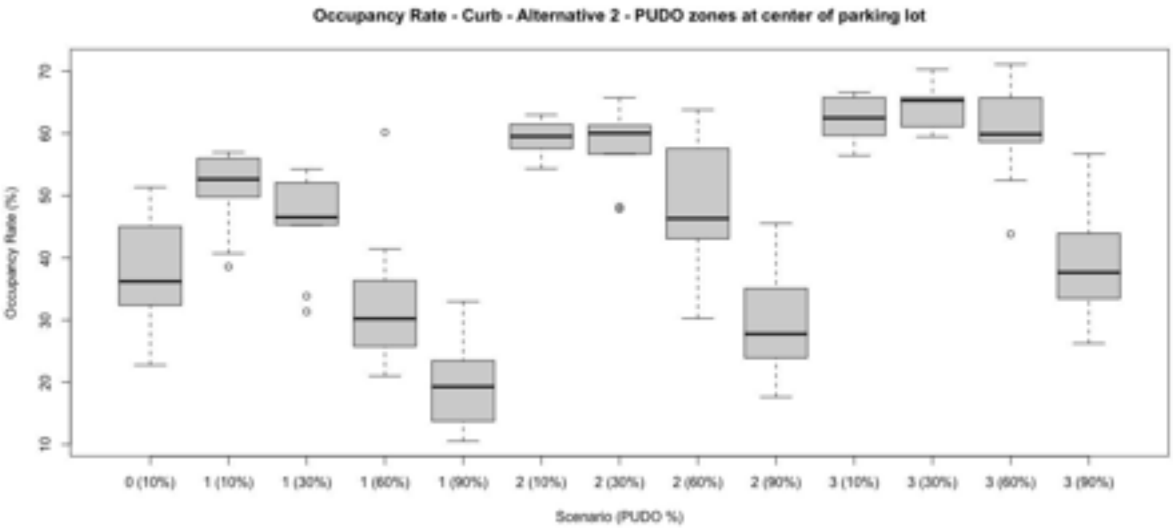

FIGURE 9-15. OCCUPANCY RATE AT THE CURB - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

OCCUPANCY RATE (DOUBLE PARKING)

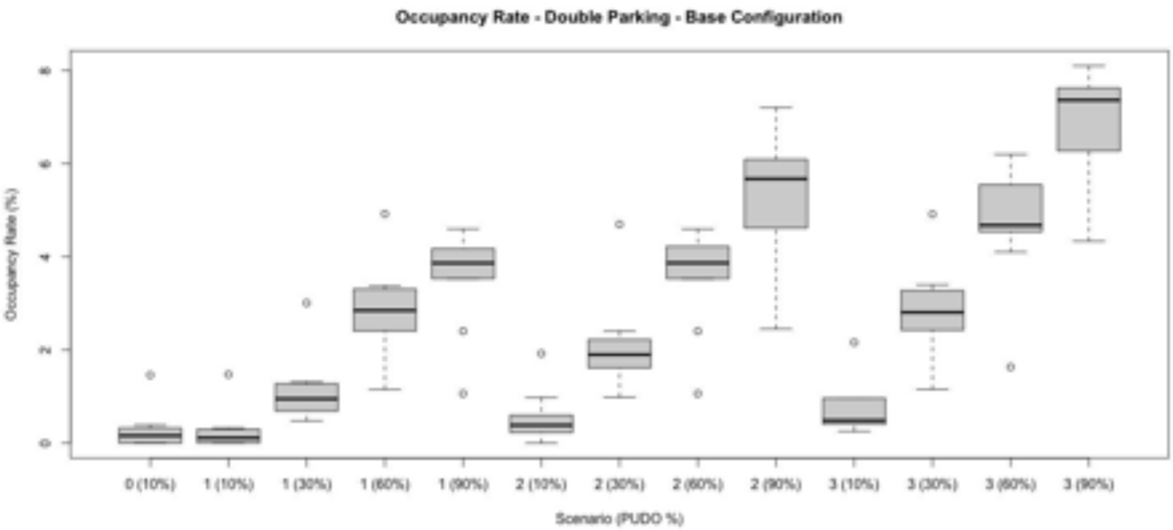

FIGURE 9-16. OCCUPANCY RATE OF DOUBLE PARKING AREA - BASE CONFIGURATION

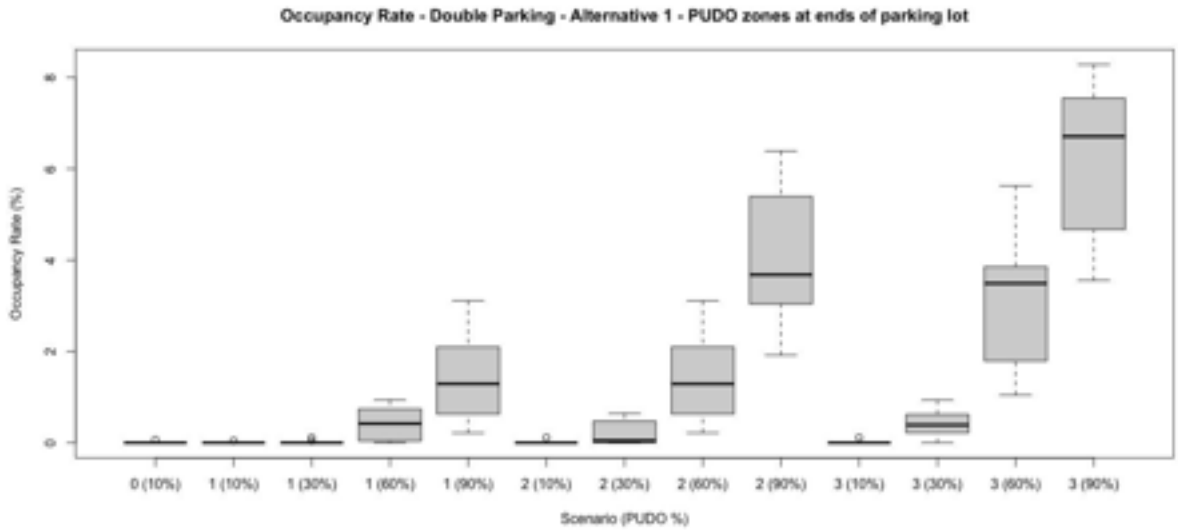

FIGURE 9-17. OCCUPANCY RATE OF DOUBLE PARKING AREA - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

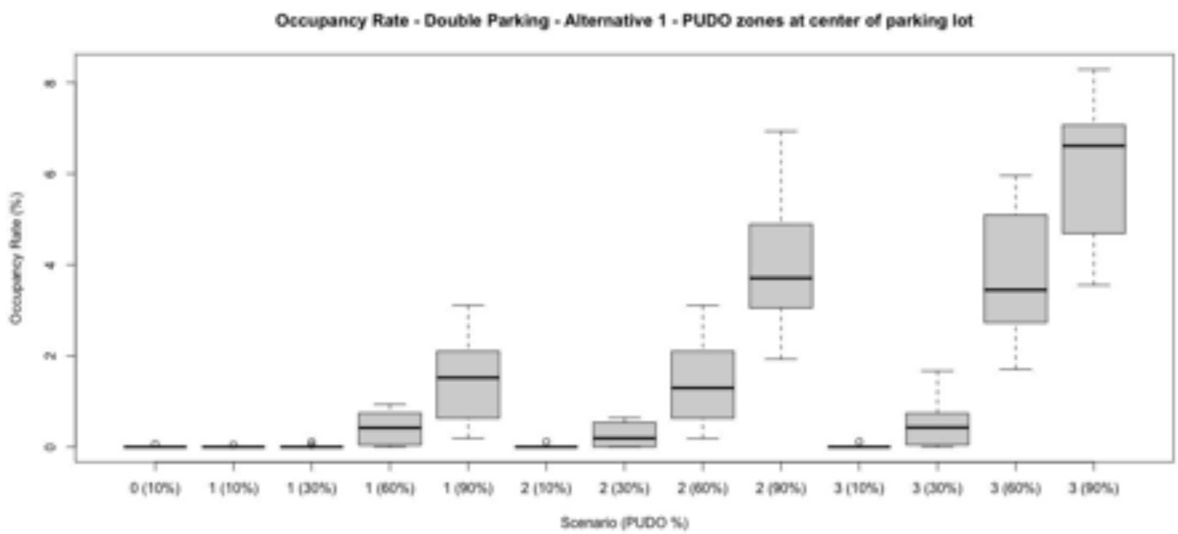

FIGURE 9-18. OCCUPANCY RATE OF DOUBLE PARKING AREA - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

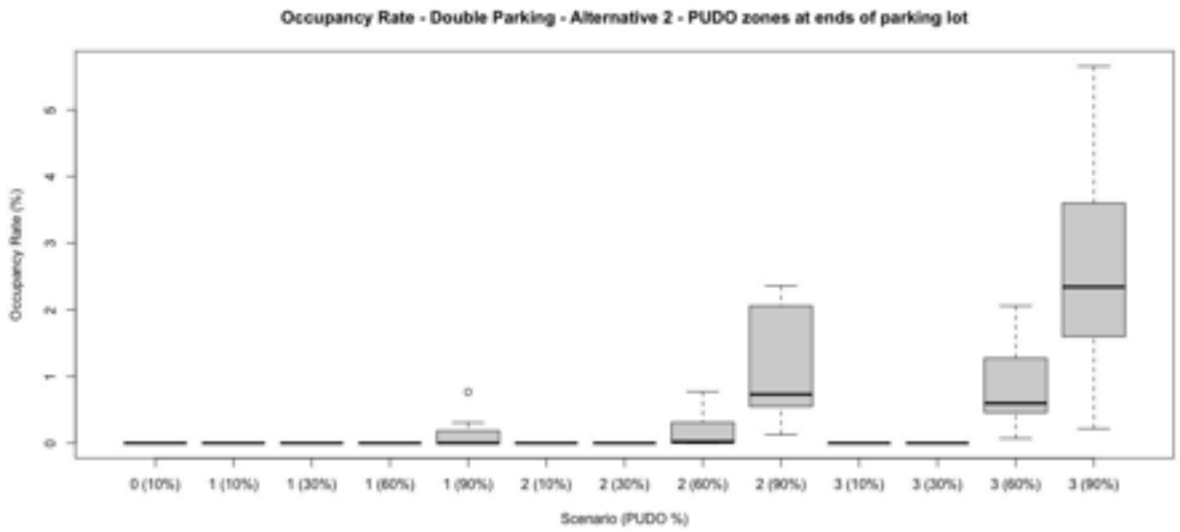

FIGURE 9-19. OCCUPANCY RATE OF DOUBLE PARKING AREA - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

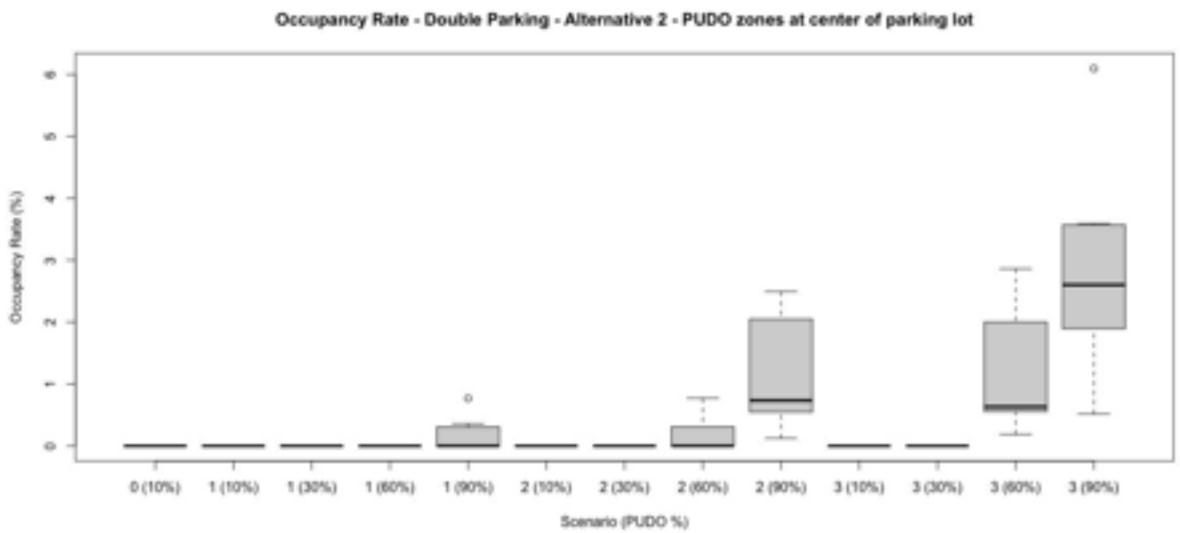

FIGURE 9-20. OCCUPANCY RATE OF DOUBLE PARKING AREA - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

NUMBER OF VEHICLES PARKED (CURB)

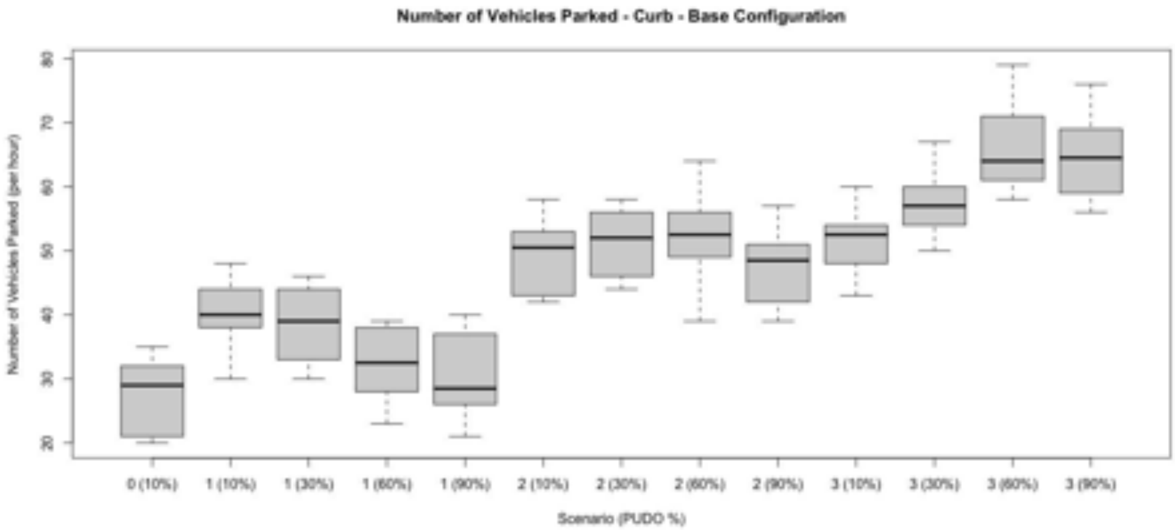

FIGURE 9-21. NUMBER OF VEHICLES PARKED AT THE CURB - BASE CONFIGURATION

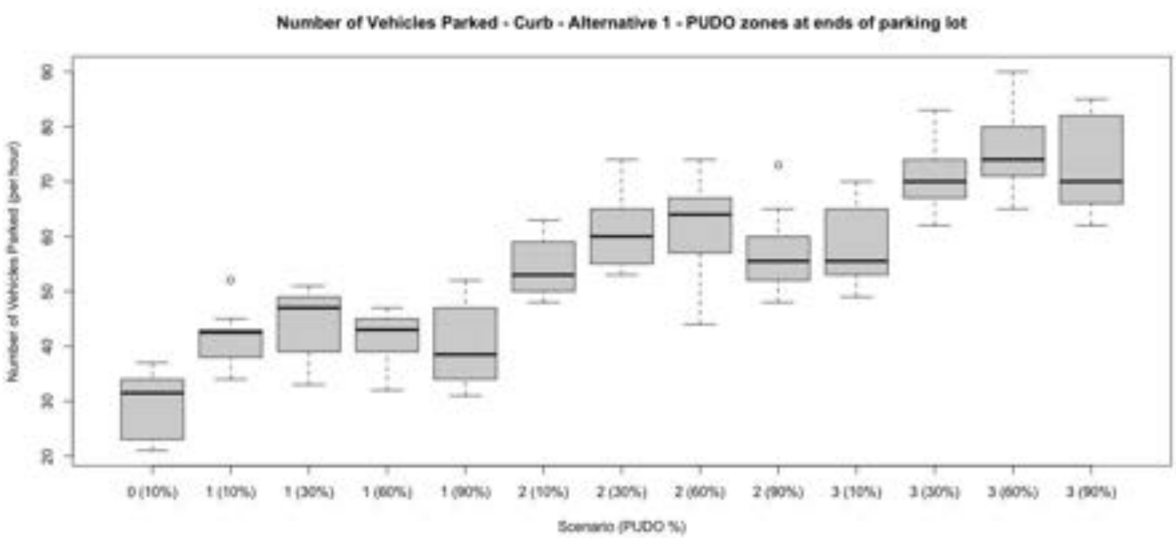

FIGURE 9-22. NUMBER OF VEHICLES PARKED AT THE CURB - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

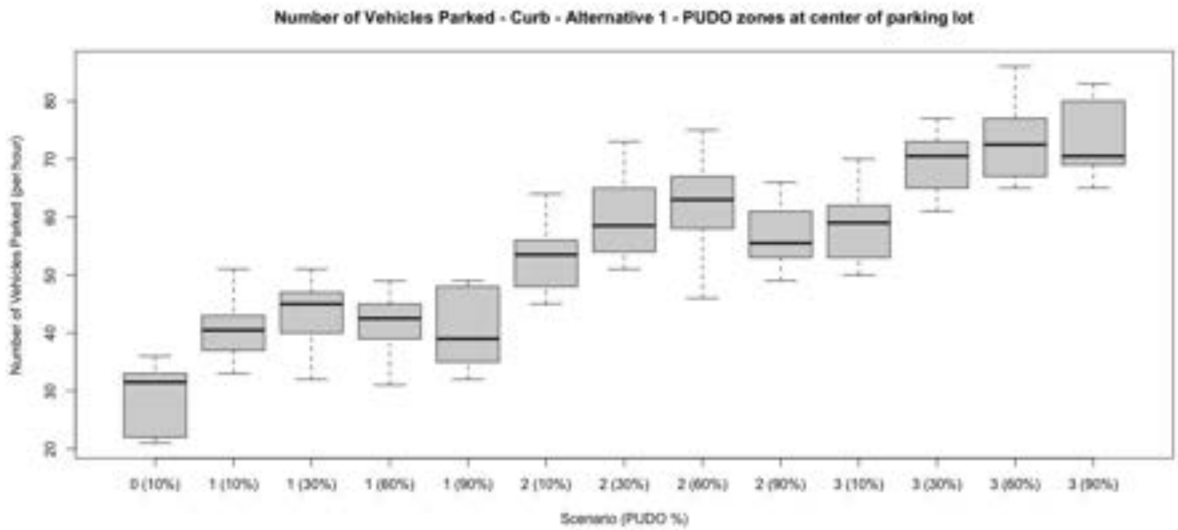

FIGURE 9-23. NUMBER OF VEHICLES PARKED AT THE CURB - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

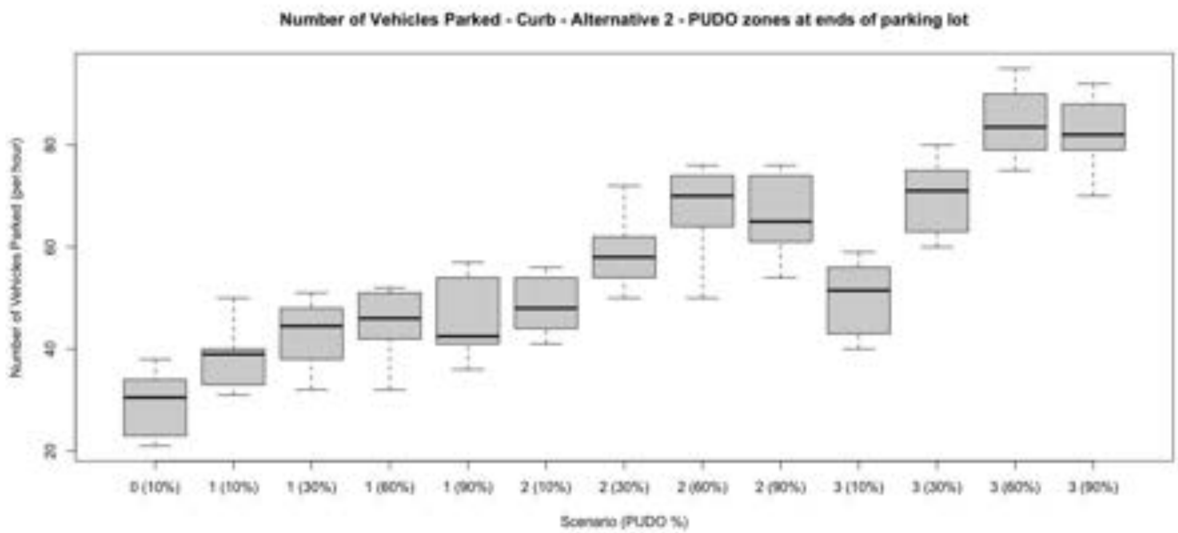

FIGURE 9-24. NUMBER OF VEHICLES PARKED AT THE CURB - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

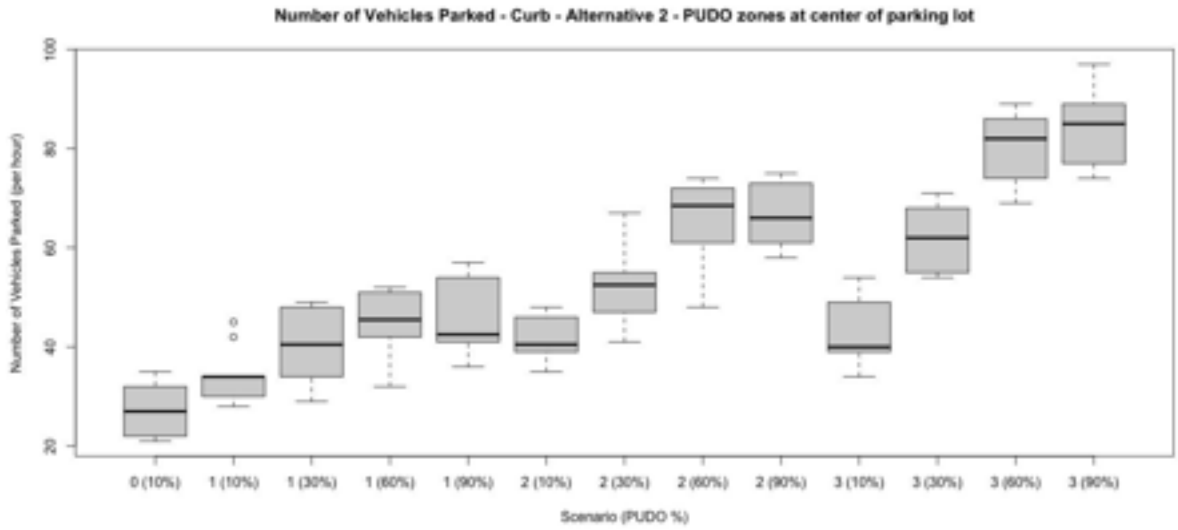

FIGURE 9-25. NUMBER OF VEHICLES PARKED AT THE CURB - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

NUMBER OF VEHICLES PARKED (DOUBLE PARKING)

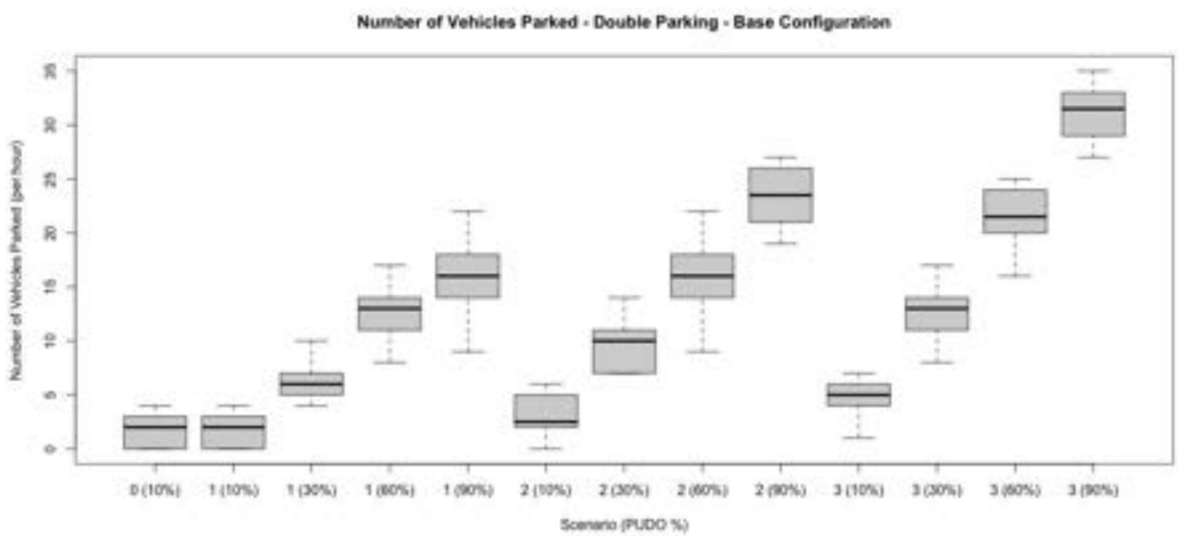

FIGURE 9-26. NUMBER OF VEHICLES DOUBLE PARKING - BASE CONFIGURATION

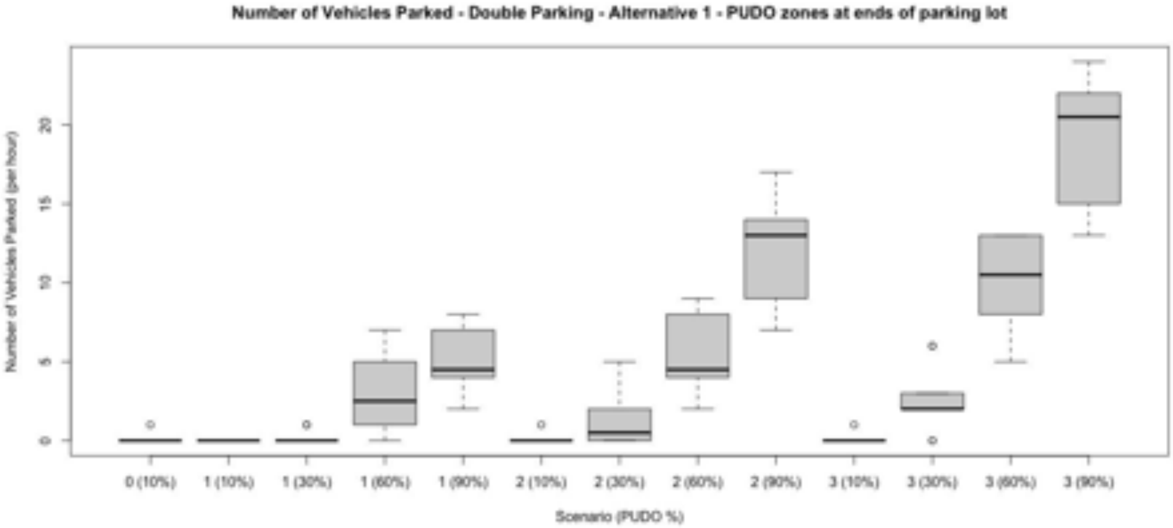

FIGURE 9-27. NUMBER OF VEHICLES DOUBLE PARKING - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

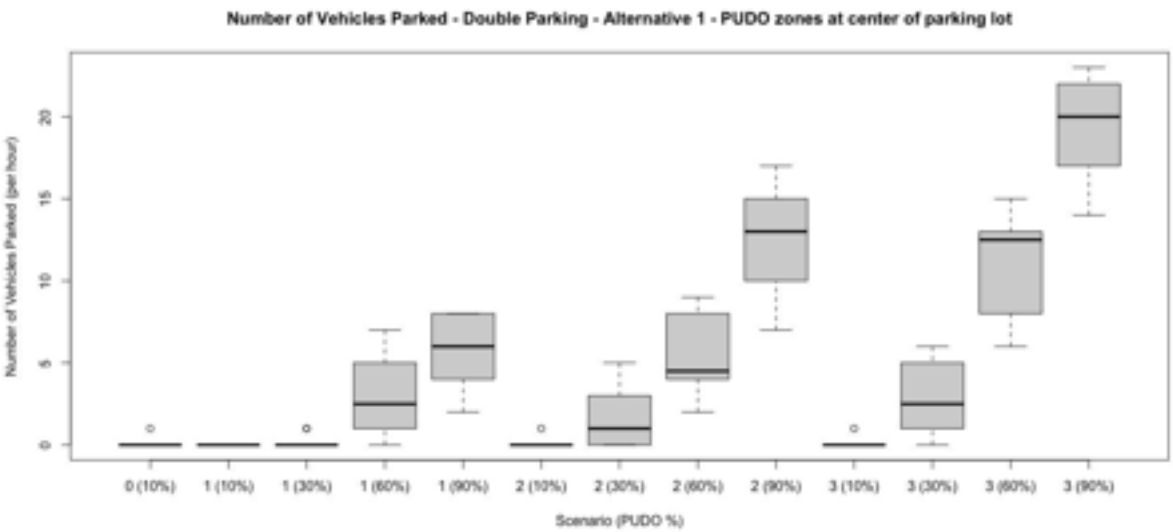

FIGURE 9-28. NUMBER OF VEHICLES DOUBLE PARKING - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

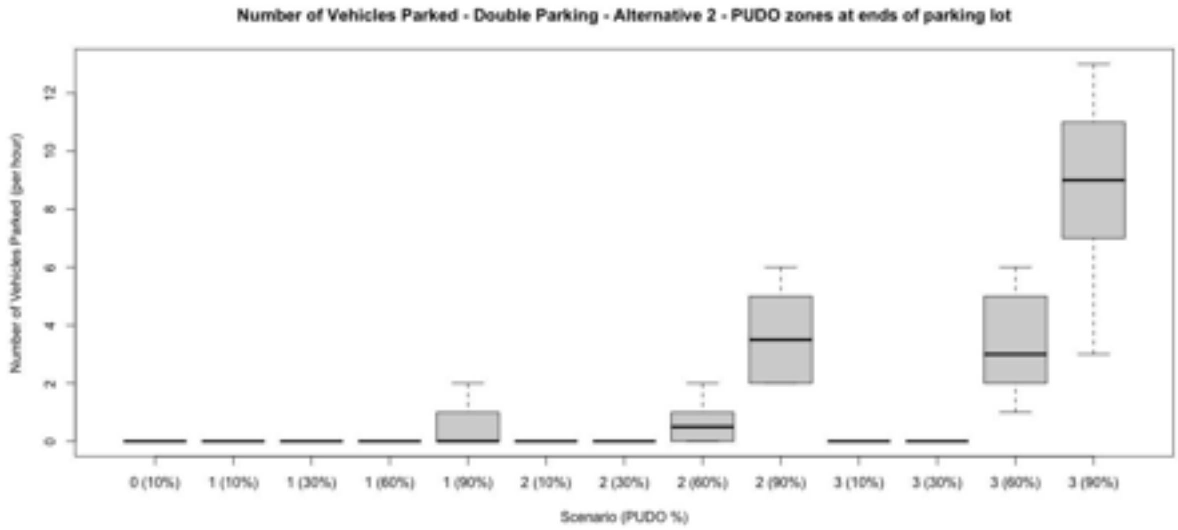

Figure 9-29. Number of vehicles double parking - Alternative Configuration 2 with PUDO zones at the ends of the parking lot

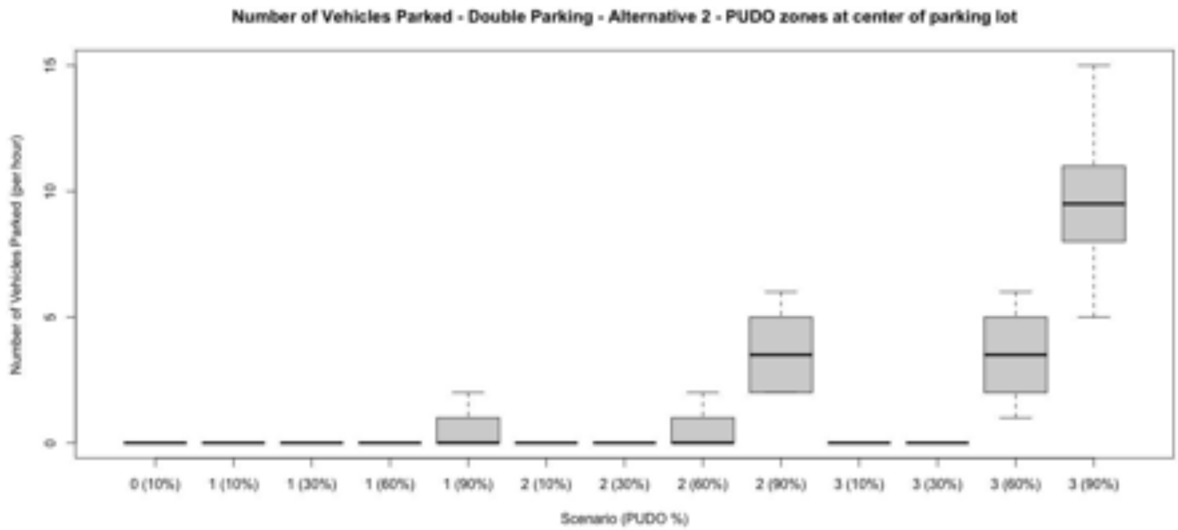

Figure 9-30. Number of vehicles double parking - Alternative Configuration 2 with PUDO zones at the center of the parking lot

PERCENTAGE OF PARKING REQUESTS DECLINED

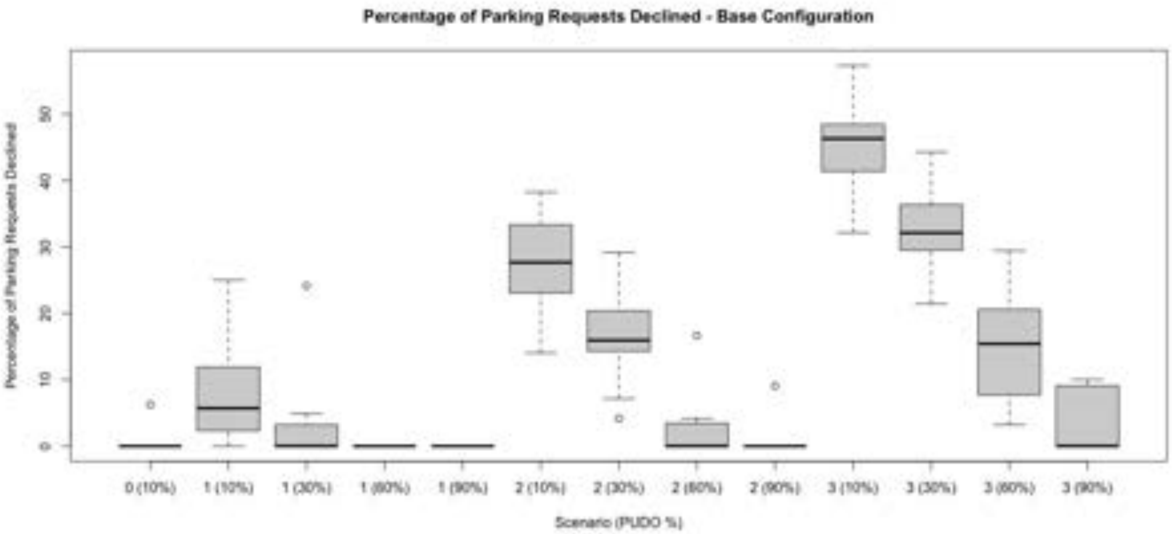

FIGURE 9-31. PERCENTAGE OF PARKING REQUESTS DECLINED - BASE CONFIGURATION

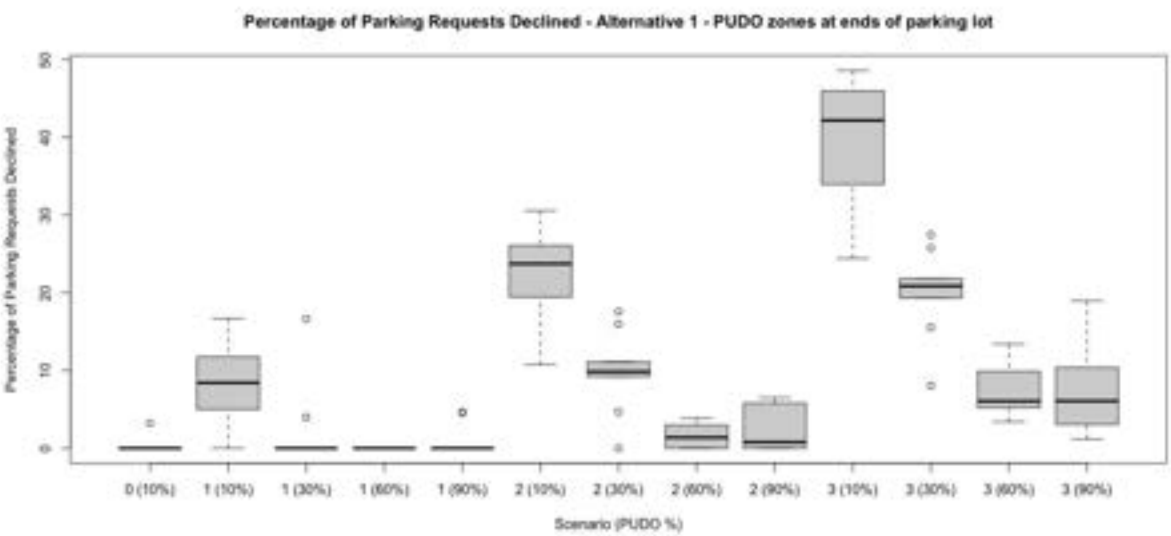

FIGURE 9-32. PERCENTAGE OF PARKING REQUESTS DECLINED - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

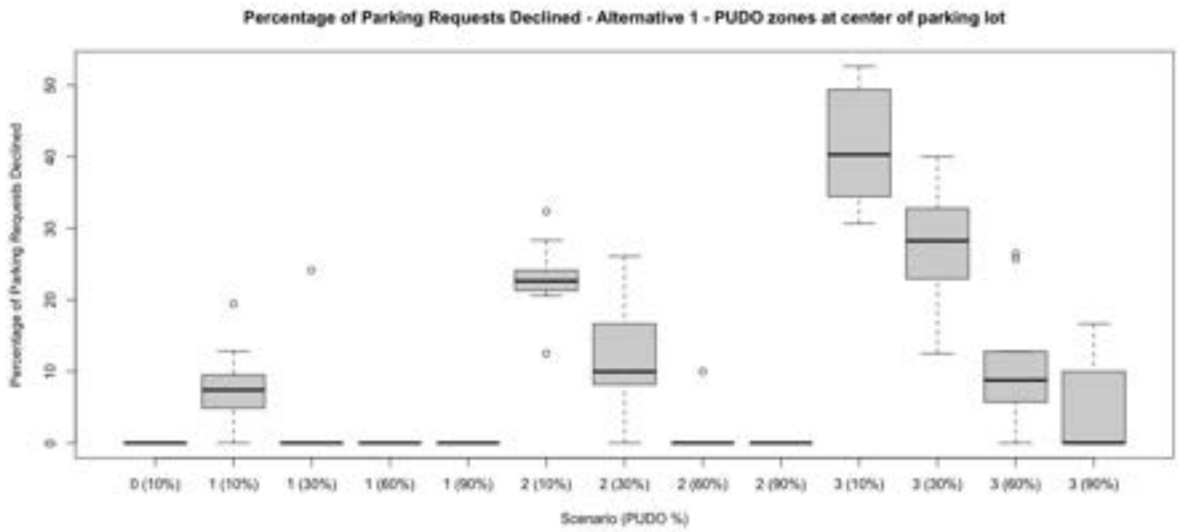

FIGURE 9-33. PERCENTAGE OF PARKING REQUESTS DECLINED - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

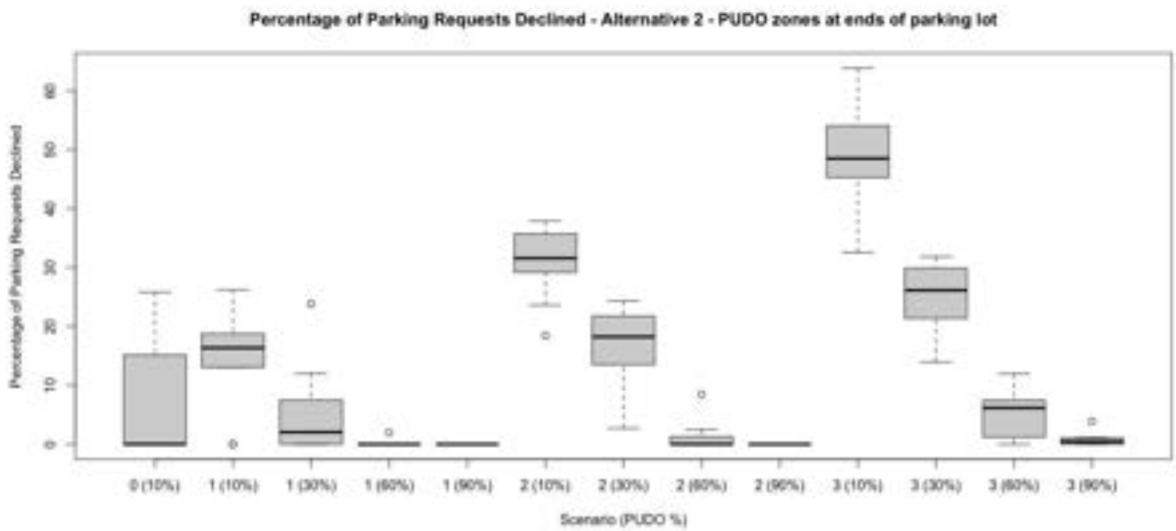

FIGURE 9-34. PERCENTAGE OF PARKING REQUESTS DECLINED - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

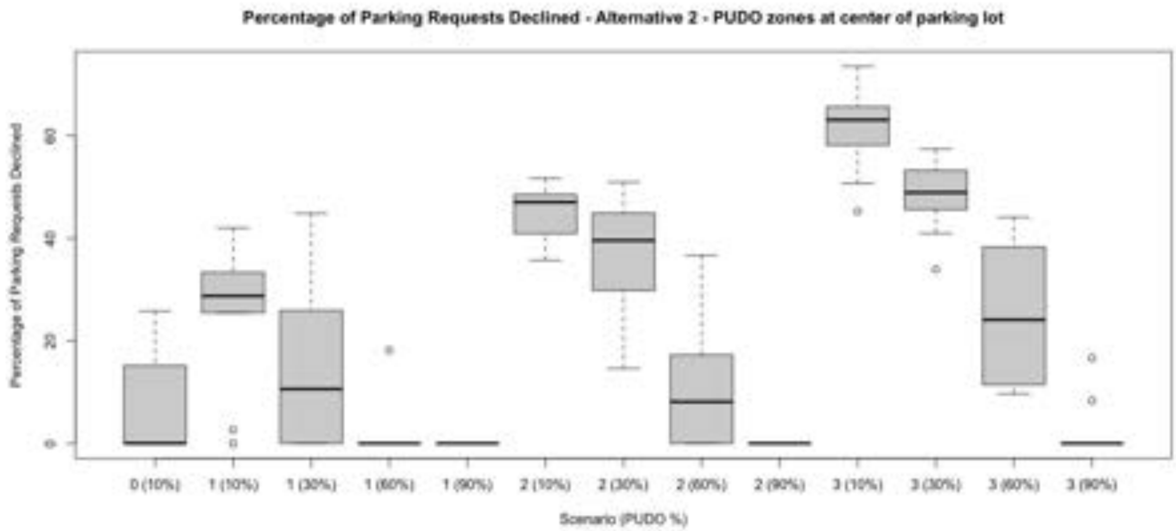

FIGURE 9-35. PERCENTAGE OF PARKING REQUESTS DECLINED - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

NUMBER OF PARKING REQUESTS DECLINED

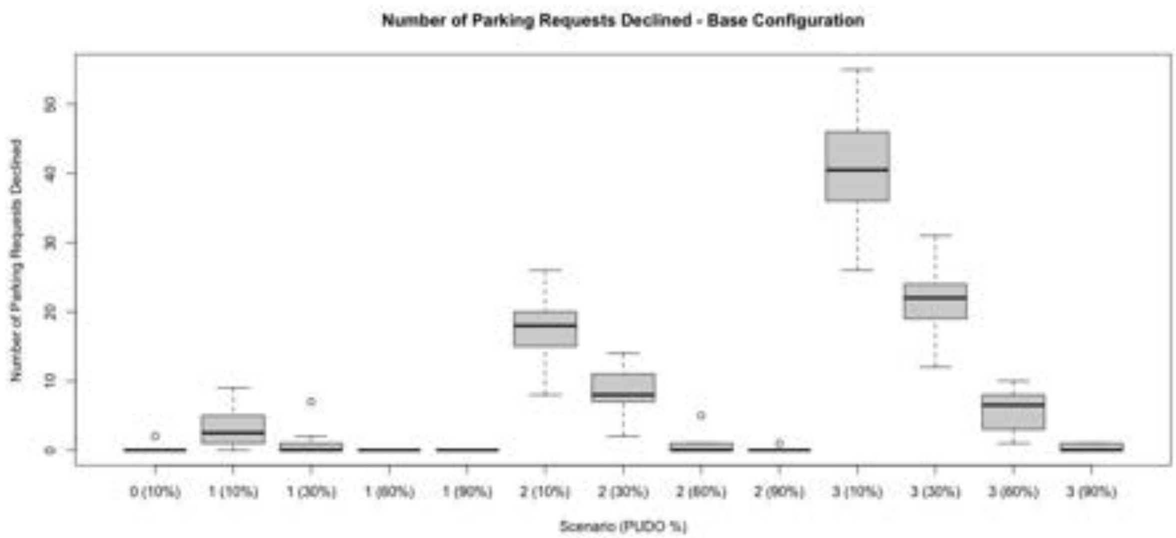

FIGURE 9-36. NUMBER OF PARKING REQUESTS DECLINED - BASE CONFIGURATION

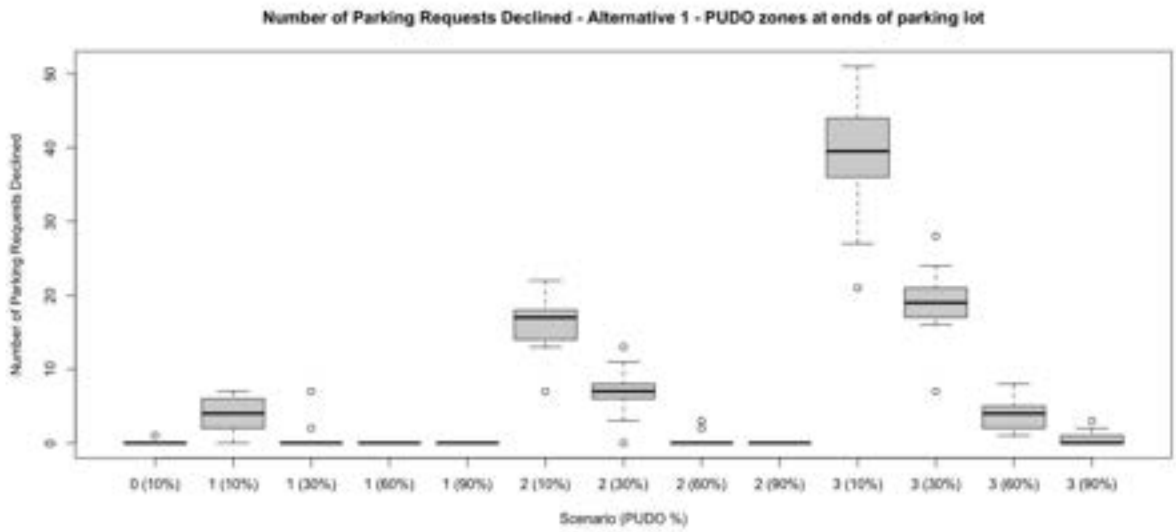

FIGURE 9-37. NUMBER OF PARKING REQUESTS DECLINED - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

FIGURE 9-38. NUMBER OF PARKING REQUESTS DECLINED - ALTERNATIVE CONFIGURATION 1 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

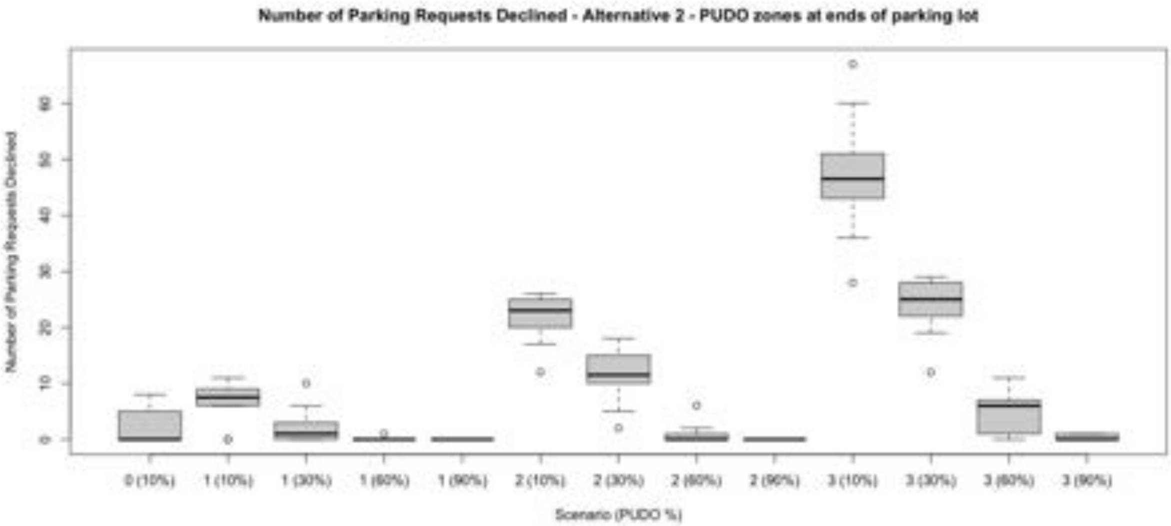

FIGURE 9-39. NUMBER OF PARKING REQUESTS DECLINED - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE ENDS OF THE PARKING LOT

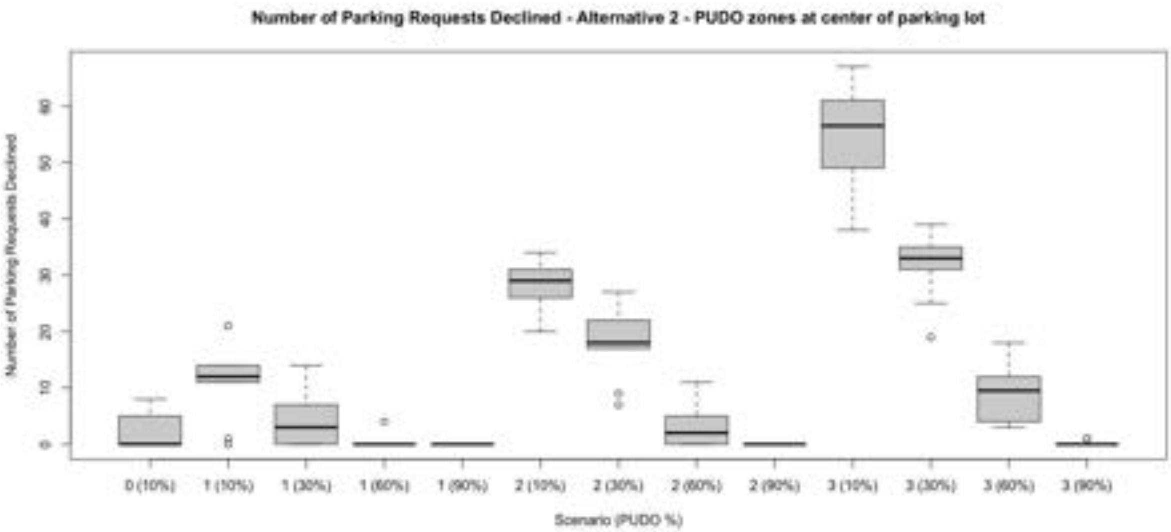

FIGURE 9-40. NUMBER OF PARKING REQUESTS DECLINED - ALTERNATIVE CONFIGURATION 2 WITH PUDO ZONES AT THE CENTER OF THE PARKING LOT

Appendix D – Wave 2 COVID-19 and Shared Mobility Survey (October 2020)

This survey was only administered online through Qualtrics

Georgia Institute of Technology invites you to take part in a survey-based research study to better understand the impact of COVID-19 on transportation services. The information you give us can help policymakers and transportation providers better understand the impacts of the pandemic, and develop services and plan communities that are more responsive to new needs.

To participate in this 10 minute survey, you must be **18 years of age or older** and **residing in the US**. As your participation is **completely voluntary**, you may stop at any time and for any reason. By continuing with this survey, you give consent to the Georgia Institute of Technology to use the information you provide as part of this research project. Your identity will never be publicly disclosed, your information will only be used for this study, and all identifying information will be kept in one secure location at the Georgia Institute of Technology. The risks involved in participating in the study are no greater than those experienced in daily life. You will not receive any direct compensation for taking this survey but we hope that the lessons learned from this research will help to make transportation planning more meaningful for people throughout the southeast and across the nation.

We will comply with any applicable laws and regulations regarding confidentiality. To make sure that this research is being carried out in the proper way, the Georgia Institute of Technology IRB may review study records. The Office of Human Research Protections may also look at study records. If you have any questions about the study, you may contact Becca Kiriazes at (407) 607-2411 or bkiriazes@gatech.edu, Dr. Kari Watkins at kari.watkins@ce.gatech.edu. If you have any questions about your rights as a research subject, you may contact Ms. Melanie Clark, Georgia Institute of Technology at (404) 894-6942.

Thank you for taking the time to complete this survey!

In this section, we are interested in understanding your comfort levels using different modes of transportation before, during, and after a COVID-19 vaccine is available. Please use the following definitions when thinking about the different travel modes.

Private ridehailing (e.g. UberX and Lyft) is an on-demand service where a rider “hails” a personal driver through a smartphone request and is taken exactly where they need to go.

Shared ridehailing with strangers (e.g. UberPool and Lyft Share) operates like private ridehailing but the vehicle is shared with other riders and may make several stops along the route.

Public transit (e.g. MARTA buses and rail) moves large numbers of passengers along a fixed route on a set schedule.

1. Before COVID-19, I would have felt comfortable using …

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. private ridehailing (e.g. UberX or Lyft services).	☐1	☐2	☐3	☐4	☐5
b. shared ridehailing with strangers (e.g. UberPool or Lyft Share).	☐1	☐2	☐3	☐4	☐5
c. public transit (e.g. MARTA buses and rail).	☐1	☐2	☐3	☐4	☐5

2. With the current COVID-19 risk, I would feel comfortable using ...

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. private ridehailing (e.g. UberX or Lyft services).	☐1	☐2	☐3	☐4	☐5
b. shared ridehailing with strangers (e.g. UberPool or Lyft Share).	☐1	☐2	☐3	☐4	☐5
c. public transit (e.g. MARTA buses and rail).	☐1	☐2	☐3	☐4	☐5

3. In the future **when a COVID-19 vaccine is available**, I will feel comfortable using...

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. private ridehailing (e.g. UberX or Lyft services).	☐1	☐2	☐3	☐4	☐5
b. shared ridehailing with strangers (e.g. UberPool or Lyft Share).	☐1	☐2	☐3	☐4	☐5
c. public transit (e.g. MARTA buses and rail).	☐1	☐2	☐3	☐4	☐5

To better understand how you travel, we would like to know your opinions on various topics. If you are not familiar with the topic, please give us your best guess. There are no “right” or “wrong” answers! Remember, when we say "ridehailing", we're referring to when you're alone in the vehicle with an on-demand driver (e.g. UberX) and when we say "shared ridehailing" we're referring to when you are in a vehicle with an on-demand driver and other passengers who are strangers (e.g. UberPool).

4. Please rate your level of agreement with each of the following statements about your **current attitudes** or preferences.

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. I consider myself to be a sociable person.	☐1	☐2	☐3	☐4	☐5
b. My friends and family would describe me as "germ conscious".	☐1	☐2	☐3	☐4	☐5
c. I'm uncomfortable being around people I don't know.	☐1	☐2	☐3	☐4	☐5
d. I always carry hand sanitizer.	☐1	☐2	☐3	☐4	☐5
e. I miss small interactions with strangers.	☐1	☐2	☐3	☐4	☐5
f. I enjoy chatting with my ridehailing driver.	☐1	☐2	☐3	☐4	☐5
g. I wear headphones while in a ridesharing vehicle to avoid interactions.	☐1	☐2	☐3	☐4	☐5
h. I enjoy chatting with fellow passengers in a shared ridehailing vehicle (e.g. UberPool).	☐1	☐2	☐3	☐4	☐5

5. Assuming the **current COVID-19 situation**, please rate your level of agreement with each of the following statements about *public transportation and COVID-19 procedures*?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. Wearing a mask should be required for all passengers riding public transit.	☐1	☐2	☐3	☐4	☐5
b. If someone **wearing a mask** sat next to me on a MARTA bus or train, I would feel u**ncomfortable** due to potential COVID-19 risk.	☐1	☐2	☐3	☐4	☐5
c. Opening the windows while riding on public transit is worth the discomfort as it reduces the risk of COVID-19.	☐1	☐2	☐3	☐4	☐5
d. I trust the precautions and extra effort taken by MARTA transit to clean and sanitize.	☐1	☐2	☐3	☐4	☐5
e. Transit services should be suspended until a vaccine for COVID-19 is found.	☐1	☐2	☐3	☐4	☐5

6. Assuming the **current COVID-19 situation**, please rate your level of agreement with each of the following statements about *ridehailing (e.g. Uber and Lyft) and COVID-19 procedures*?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. I would feel **comfortable** using a ridehailing vehicle if I was equipped with disinfectant sprays and wipes to sanitize the vehicle before and after each ride.	☐1	☐2	☐3	☐4	☐5
b. Shared ridehailing with strangers services (e.g. UberPool, Lyft Share) should be suspended until a vaccine for COVID-19 is found.	☐1	☐2	☐3	☐4	☐5
c. I would feel **comfortable** riding with a stranger **wearing a mask** in a shared ridehailing vehicle (like UberPool) as long as there is a seat in between passengers.	☐1	☐2	☐3	☐4	☐5
d. If my ridehailing driver wasn't wearing a mask, I would request a new vehicle.	☐1	☐2	☐3	☐4	☐5
e. Opening the windows while riding in a ridehailing vehicle is worth the discomfort as it reduces the risk of COVID-19.	☐1	☐2	☐3	☐4	☐5
f. If there was already a passenger wearing a mask in the back seat of a shared ridehail (e.g. UberPool), I would sit in the front passenger seat.	☐1	☐2	☐3	☐4	☐5

7. Do you have any additional thoughts or experiences related to the **use of ridehailing and procedures related to COVID-19**? If you would like to share them, please do below.

____

Think back to life **before the COVID-19 pandemic** and the various trips you made in the; to work or school, restaurants and stores, casual social events, doctors' appointments, large concerts or sporting events, sightseeing, and more.

8. Please indicate how often you typically made these trips **before the COVID-19 pandemic** using each of the following means of travel. If you are unsure, please make your best guess.

	Never	Less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week
a. Personal vehicle, alone	☐1	☐2	☐3	☐4	☐5	☐6
b. Personal vehicle, with others	☐1	☐2	☐3	☐4	☐5	☐6
c. Private ridehailing (e.g. UberX or Lyft services)	☐1	☐2	☐3	☐4	☐5	☐6
d. Shared ridehailing with strangers (e.g. UberPool or Lyft Share)	☐1	☐2	☐3	☐4	☐5	☐6
e. MARTA bus	☐1	☐2	☐3	☐4	☐5	☐6
f. MARTA rail	☐1	☐2	☐3	☐4	☐5	☐6
g. Personal bike or e-bike	☐1	☐2	☐3	☐4	☐5	☐6
h. Shared bike or e-bike (e.g. Relay)	☐1	☐2	☐3	☐4	☐5	☐6
i. Shared e-scooter (e.g. Bird, Spin)	☐1	☐2	☐3	☐4	☐5	☐6
j. Walk	☐1	☐2	☐3	☐4	☐5	☐6

9. Before the COVID-19 pandemic, how often did you use the following technologies instead of making a trip?

	Never	Less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week
a. Telework (e.g. remote working)	☐1	☐2	☐3	☐4	☐5	☐6
b. Online Shopping (e.g. Amazon Delivery)	☐1	☐2	☐3	☐4	☐5	☐6
c. Food Delivery Services (e.g. UberEats)	☐1	☐2	☐3	☐4	☐5	☐6
d. Video Chat with friends or family (e.g. Zoom)	☐1	☐2	☐3	☐4	☐5	☐6

The recent COVID-19 pandemic has heavily impacted the way people work, socialize, and travel. Think back to the various trips you made in the **past month**; to work or school, restaurants and stores, casual social events, doctors' appointments, large concerts or sporting events, sightseeing, and more.

10. Please indicate how often you typically made these trips **in the past month during the COVID-19 pandemic** using each of the following means of travel. If you are unsure, please make your best guess

	Never	Less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week
a. Personal vehicle, alone	☐1	☐2	☐3	☐4	☐5	☐6
b. Personal vehicle, with others	☐1	☐2	☐3	☐4	☐5	☐6
c. Private ridehailing (e.g. UberX or Lyft services)	☐1	☐2	☐3	☐4	☐5	☐6
d. Shared ridehailing with strangers (e.g. UberPool or Lyft Share)	☐1	☐2	☐3	☐4	☐5	☐6
e. MARTA bus	☐1	☐2	☐3	☐4	☐5	☐6
f. MARTA rail	☐1	☐2	☐3	☐4	☐5	☐6
g. Personal bike or e-bike	☐1	☐2	☐3	☐4	☐5	☐6
h. Shared bike or e-bike (e.g. Relay)	☐1	☐2	☐3	☐4	☐5	☐6
i. Shared e-scooter (e.g. Bird, Spin)	☐1	☐2	☐3	☐4	☐5	☐6
j. Walk	☐1	☐2	☐3	☐4	☐5	☐6

11. In the past month, how often did you use the following technologies <u>instead of making a trip</u>?

	Never	Less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week
a. Telework (e.g. remote working)	☐1	☐2	☐3	☐4	☐5	☐6
b. Online Shopping (e.g. Amazon Delivery)	☐1	☐2	☐3	☐4	☐5	☐6
c. Food Delivery Services (e.g. UberEats)	☐1	☐2	☐3	☐4	☐5	☐6
d. Video Chat with friends or family (e.g. Zoom)	☐1	☐2	☐3	☐4	☐5	☐6

12. Please rate your level of agreement with each of the following statements about your **change in transportation behavior.**

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. I travel more now simply to "get out" instead of traveling for a reason.	☐1	☐2	☐3	☐4	☐5
b. If I could work from home and not commute, I would choose to work from home.	☐1	☐2	☐3	☐4	☐5
c. If I could commute and go into work, I would choose to go into my office.	☐1	☐2	☐3	☐4	☐5
d. If I could attend social events like festivals, concerts, or sporting events, I would attend them.	☐1	☐2	☐3	☐4	☐5

13. I have changed the way I travel because my typical transit service has changed (e.g. MARTA bus)?

☐1 Yes ☐2 No

14. I have changed the way I travel because shared ridehailing is not available (e.g. UberPOOL, Lyft Share)?

☐1 Yes ☐2 No

15. Do you have any *additional thoughts or trip experiences* related to changes in your transportation behavior related to the COVID-19 pandemic? If you would like to share them, please do so below.

13b. How has your local transit service changed? (Select all that apply)

☐1 My bus route is no longer in service ☐2 My bus route has more frequent service.

☐3 My bus route has less frequent service ☐4 I traveled more on the bus because it was free.

☐5 My rail service has less frequent service.

☐6 Other ___________________________

13b. Do you have any ***additional thoughts or trip experiences*** related to your use of **transit and COVID-19**? If you would like to share them, please do so below.

We have reached the final section of the survey! To help us project the responses from this small sample to the population as a whole, we'd like to ask you a few **background questions**.

16. In what year were you born? (e.g. 1975) ____

17. What is your ***educational background*****?** Please select the highest level attained.

☐1 Some grade/high school ☐2 Completed high school or GED ☐3 Some college or technical school ☐4 Bachelor's degree(s) ☐5 Graduate degree(s) (e.g. MS, PhD, MBA) ☐6Professional degree(s) (e.g. JD, MD, DDS)

18. What is your ***gender*** identity?

☐1 Male ☐2 Female ☐3 Prefer to self-describe

19. Are you Hispanic or Latino/a?

☐1 Yes ☐2 No

20. How would you describe your ***race***? Please check ALL that apply to you.

☐1 Asian or Pacific Islander ☐2 Black/African American ☐3 Native American

☐4 White/Caucasian ☐5 Other (please specify) __________________________________

21. What is the 5-digit ***zip code*** for your residence (i.e.the place where you live most of the time throughout the year)? (e.g. 30322) __________________________________

22. What is your **employment situation before COVID-19**? Please check ALL that apply.

☐1 I was a full-time student ☐2 I was a part-time student ☐3 I worked full-time

☐4 I worked part-time ☐5 I was retired ☐6 I was a homemaker/unpaid caregiver ☐7 I did not work ☐8 Other _____________________

23. What is your **current employment situation**? Please check ALL that apply.

☐1 I am a full-time student ☐2 I am a part-time student ☐3 I work full-time

☐4 I work part-time ☐5 I am retired ☐6 I am a homemaker/unpaid caregiver

☐7 I do not work ☐8 Other _______________________

24. Please check the category that contains your approximate 2019 annual ***household income*** before taxes. By "household" we mean "people who live together and share at least some financial resources" (housemates/roommates are usually not considered members of the same household).

☐1 Less than $25,000 ☐2 $25,000 to $49,99 ☐3 $50,000 to $74,999

☐4 $75,000 to $99,999 ☐5 $100,000 to $149,999 ☐6 $150,000 or more

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As response to the COVID pandemic continues, we would like to send you two additional short surveys about your willingness to share spaces. To help us reach you, please provide us with your **email address**. This information will be kept completely confidential, and will never be used for any other purpose.

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Thank you again for taking the time to complete our survey!

We appreciate your dedication and time to this project. If you have any additional questions, please contact our research team at survey@ce.gatech.edu.

If you have any comments or questions you'd like to leave us about the survey or related topics, please do so below.

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Appendix F – Wave 1 COVID-19 and Shared Mobility Survey, (October 2021)

This survey was only administered online through Qualtrics.

We are reaching out to you again to invite you to take part in a survey-based research study to better understand the impact of COVID-19 on transportation services. This follow-up survey to the Fall 2021 Georgia Institute of Technology COVID-19 Transportation Survey will help us understand the dynamic impact of COVID-19 on mobility choices. Thank you for your participation in the previous survey and we appreciate your continued response!

To participate in this 8 minute survey, you must be 18 years of age or older and residing in the US. As your participation is completely voluntary, you may stop at any time and for any reason. By continuing with this survey, you give consent to the Georgia Institute of Technology to use the information you provide as part of this research project. Your identity will never be publicly disclosed, your information will only be used for this study, and all identifying information will be kept in one secure location at the Georgia Institute of Technology. The risks involved in participating in the study are no greater than those experienced in daily life. You will not receive any direct compensation for taking this survey but we hope that the lessons learned from this research will help to make transportation planning more meaningful for people throughout the southeast and across the nation.

We will comply with any applicable laws and regulations regarding confidentiality. To make sure that this research is being carried out in the proper way, the Georgia Institute of Technology IRB may review study records. The Office of Human Research Protections may also look at study records. If you have any questions about the study, you may contact Becca Kiriazes at (407) 607-2411 or bkiriazes@gatech.edu, or Dr. Kari Watkins at kari.watkins@ce.gatech.edu. If you have any questions about your rights as a research subject, you may contact Ms. Melanie Clark, Georgia Institute of Technology at (404) 894-6942.

Thank you for taking the time to complete this survey!

In this section, we are interested in understanding your comfort levels using different modes of transportation at three different points in time: (1) when COVID-19 cases were low over the summer of 2021, (2) the current moment, and (3) a year from now (in fall 2022). Please use the following definitions when thinking about the different travel modes.

Private ridehailing (e.g. UberX and Lyft) is an on-demand service where a rider "hails" a personal driver through a smartphone request and is taken exactly where they need to go.

Shared ridehailing with strangers (e.g. UberPool and Lyft Share) operates like private ridehailing but the vehicle is shared with other riders and may make several stops along the route.

Public transit (e.g. MARTA buses and rail) moves large numbers of passengers along a fixed route on a set schedule.

1. When COVID-19 cases were low *(over the summer in 2021)*, I would have felt comfortable using …

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. private ridehailing (e.g. UberX or Lyft services).	☐1	☐2	☐3	☐4	☐5
b. shared ridehailing with strangers (e.g. UberPool or Lyft Share).	☐1	☐2	☐3	☐4	☐5
c. public transit (e.g. MARTA buses and rail).	☐1	☐2	☐3	☐4	☐5

2. With the current COVID-19 situation, I would feel comfortable using ...

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. private ridehailing (e.g. UberX or Lyft services).	☐1	☐2	☐3	☐4	☐5
b. shared ridehailing with strangers (e.g. UberPool or Lyft Share).	☐1	☐2	☐3	☐4	☐5
c. public transit (e.g. MARTA buses and rail).	☐1	☐2	☐3	☐4	☐5

3. In the future *(a year from now in Fall 2022)*, I will feel comfortable using...

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. private ridehailing (e.g. UberX or Lyft services).	☐1	☐2	☐3	☐4	☐5
b. shared ridehailing with strangers (e.g. UberPool or Lyft Share).	☐1	☐2	☐3	☐4	☐5
c. public transit (e.g. MARTA buses and rail).	☐1	☐2	☐3	☐4	☐5

To better understand how you travel, we would like to know your opinions on various topics. If you are not familiar with the topic, please give us your best guess. There are no “right” or “wrong” answers! Remember, when we say "private ridehailing", we're referring to when you're alone in the vehicle with an on-demand driver (e.g. UberX) and when we say "shared ridehailing" we're referring to when you are in a vehicle with an on-demand driver and other passengers who are strangers (e.g. UberPool).

4. Please rate your level of agreement with each of the following statements about your **current attitudes** or preferences.

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. I consider myself to be a sociable person.	☐1	☐2	☐3	☐4	☐5
b. My friends and family would describe me as "germ conscious".	☐1	☐2	☐3	☐4	☐5
c. I’m uncomfortable being around people I don’t know.	☐1	☐2	☐3	☐4	☐5
d. I always carry hand sanitizer.	☐1	☐2	☐3	☐4	☐5
e. I enjoy chatting with my ridehailing driver.	☐1	☐2	☐3	☐4	☐5
f. I enjoy chatting with fellow passengers in a shared ridehailing vehicle (e.g. UberPool).	☐1	☐2	☐3	☐4	☐5

5. Assuming the **current COVID-19 situation**, please rate your level of agreement with each of the following statements about *public transportation and COVID-19 procedures*?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. If someone **without a mask** sat next to me on a MARTA bus or train, I would feel **uncomfortable** due to potential COVID-19 risk.	☐1	☐2	☐3	☐4	☐5
b. If someone **wearing a mask** sat next to me on a MARTA bus or train, I would feel **uncomfortable** due to potential COVID-19 risk.	☐1	☐2	☐3	☐4	☐5
c. I trust the precautions and extra effort taken by MARTA transit to clean and sanitize.	☐1	☐2	☐3	☐4	☐5
d. Transit services should be suspended due to the potential COVID-19 risk.	☐1	☐2	☐3	☐4	☐5

6. Do you have any additional thoughts or experiences related to the use of **transit and procedures related to COVID-19**? If you would like to share them, please do below.

____

7. Assuming the **current COVID-19 situation**, please rate your level of agreement with each of the following statements about *ridehailing (e.g. Uber and Lyft) and COVID-19 procedures*?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. I would feel **comfortable** using a ridehailing vehicle if I was equipped with disinfectant sprays and wipes to sanitize the vehicle before and after each ride.	☐1	☐2	☐3	☐4	☐5
b. If my ridehailing driver wasn't wearing a mask, I would request a new vehicle.	☐1	☐2	☐3	☐4	☐5
c. Opening the windows while riding in a ridehailing vehicle is worth the discomfort as it reduces the risk of COVID-19.	☐1	☐2	☐3	☐4	☐5

d. I would feel **comfortable** riding with a stranger **wearing a mask** in a shared ridehailing vehicle (like UberPool) as long as there is a seat in between passengers.	☐1	☐2	☐3	☐4	☐5
e. I would feel **comfortable** riding with a stranger who **isn't wearing a mask** in a shared ridehailing vehicle (like UberPool), as long as there is a seat in between passengers.	☐1	☐2	☐3	☐4	☐5
f. Shared ridehailing services (those with strangers e.g. UberPool, Lyft Share) should be suspended due to the potential COVID-19 risk.	☐1	☐2	☐3	☐4	☐5

8. Do you have any additional thoughts or experiences related to the **use of ridehailing and procedures related to COVID-19**? If you would like to share them, please do below.

____

9. Please rate your level of agreement with each of the following statements *about how COVID-19 has impacted your activities.* Please use "normal" to define your life pre-pandemic.

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
a. My activities **had already** returned to "normal" over the summer when COVID-19 cases were low.	☐1	☐2	☐3	☐4	☐5
b. My current activities have continued despite the increase in COVID-19 cases.	☐1	☐2	☐3	☐4	☐5
c. I expect my activities to be "normal" next year (Fall 2022).	☐1	☐2	☐3	☐4	☐5
d. I think COVID-19 will forever change my use of transportation.	☐1	☐2	☐3	☐4	☐5
f. I would feel **comfortable** sharing small indoor spaces (like an extended elevator ride) with strangers **wearing a mask**.	☐1	☐2	☐3	☐4	☐5
g. I would feel **comfortable** sharing small indoor spaces (like an extended elevator ride) with strangers who are **not wearing a mask**.	☐1	☐2	☐3	☐4	☐5
h. Now that a vaccine is available, I am less concerned about COVID-19	☐1	☐2	☐3	☐4	☐5

10. Please select the option that best describes your interest in the COVID-19 vaccine:

☐1 I have received the COVID-19 vaccine and already have my booster dose.
☐2 I have received the COVID-19 vaccine and I interested in getting my booster dose.
☐3 I have received the COVID-19 vaccine and not currently interested my booster dose.
☐4 I have not received the COVID-19 vaccine but already had COVID.
☐5 I have not received the COVID-19 vaccine and have not already had COVID.
☐6 Prefer not to answer.

11. You indicated that you "**XXX**" with the statement "*COVID-19 will forever change my use of transportation*". If you would like to share an explanation why you believe this, please do below.

____

Think back to the various trips you made in the **summer of 2021 when COVID-19 cases were low**; to work or school, restaurants and stores, casual social events, doctors' appointments, large concerts or sporting events, sightseeing, and more. Then think about **how** you made those trips; by car, bus, walking, and more.

12. Please indicate how often you typically made these trips **in the average month during the summer of 2021 when COVID-19 cases were low** using each of the following means of travel. If you are unsure, please make your best guess.

	Never	Less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week
a. Personal vehicle, alone	☐1	☐2	☐3	☐4	☐5	☐6
b. Personal vehicle, with others	☐1	☐2	☐3	☐4	☐5	☐6
c. Private ridehailing (e.g. UberX or Lyft services)	☐1	☐2	☐3	☐4	☐5	☐6

d. Shared ridehailing with strangers (e.g. UberPool or Lyft Share)	☐1	☐2	☐3	☐4	☐5	☐6
e. MARTA bus	☐1	☐2	☐3	☐4	☐5	☐6
f. MARTA rail	☐1	☐2	☐3	☐4	☐5	☐6
g. Personal bike or e-bike	☐1	☐2	☐3	☐4	☐5	☐6
h. Shared bike or e-bike (e.g. Relay)	☐1	☐2	☐3	☐4	☐5	☐6
i. Shared e-scooter (e.g. Bird, Spin)	☐1	☐2	☐3	☐4	☐5	☐6
j. Walk	☐1	☐2	☐3	☐4	☐5	☐6

13. In Summer 2021, how often did you use the following technologies <u>instead of making a trip</u>?

	Never	Less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week
a. Telework (e.g. remote working)	☐1	☐2	☐3	☐4	☐5	☐6
b. Online Shopping (e.g. Amazon Delivery)	☐1	☐2	☐3	☐4	☐5	☐6
c. Food Delivery Services (e.g. UberEats)	☐1	☐2	☐3	☐4	☐5	☐6
d. Video Chat with friends or family (e.g. Zoom)	☐1	☐2	☐3	☐4	☐5	☐6

Think back to the various trips you made in the **past month**; to work or school, restaurants and stores, casual social events, doctors' appointments, large concerts or sporting events, sightseeing, and more. Then think about **how** you made those trips; by car, bus, walking, and more.

14. Please indicate how often you typically made these trips **in the past month** using each of the following means of travel. If you are unsure, please make your best guess.

	Never	Less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week
a. Personal vehicle, alone	☐1	☐2	☐3	☐4	☐5	☐6
b. Personal vehicle, with others	☐1	☐2	☐3	☐4	☐5	☐6
c. Private ridehailing (e.g. UberX or Lyft services)	☐1	☐2	☐3	☐4	☐5	☐6
d. Shared ridehailing (e.g. UberPool or Lyft Share)	☐1	☐2	☐3	☐4	☐5	☐6
e. MARTA bus	☐1	☐2	☐3	☐4	☐5	☐6
f. MARTA rail	☐1	☐2	☐3	☐4	☐5	☐6
g. Personal bike or e-bike	☐1	☐2	☐3	☐4	☐5	☐6
h. Shared bike or e-bike (e.g. Relay)	☐1	☐2	☐3	☐4	☐5	☐6
i. Shared e-scooter (e.g. Bird, Spin)	☐1	☐2	☐3	☐4	☐5	☐6
j. Walk	☐1	☐2	☐3	☐4	☐5	☐6

15. In the past month, how often did you use the following technologies <u>instead of making a trip</u>?

	Never	Less than once a month	1-3 times a month	1-2 times a week	3-4 times a week	5 or more times a week

a. Telework (e.g. remote working)	☐1	☐2	☐3	☐4	☐5	☐6
b. Online Shopping (e.g. Amazon Delivery)	☐1	☐2	☐3	☐4	☐5	☐6
c. Food Delivery Services (e.g. UberEats)	☐1	☐2	☐3	☐4	☐5	☐6
d. Video Chat with friends or family (e.g. Zoom)	☐1	☐2	☐3	☐4	☐5	☐6

16. Shared ridehailing services (with strangers e.g. UberPool and Lyft Share) have been temporarily suspended in Atlanta since March 2020. Have you changed the way you travel because shared ridehailing is not available (e.g. UberPOOL, Lyft Share)?

☐1 Yes ☐2 No

17. Do you have any *additional thoughts or trip experiences* related to changes in your transportation behavior related to the COVID-19 pandemic? If you would like to share them, please do so below.

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We have reached the final section of the survey! To help us project the responses from this small sample to the population as a whole, we'd like to ask you a few **background questions**.

18. In what year were you born? (e.g. 1975) ______________________________________

19. What is your ***educational background*?** Please select the highest level attained.

☐1 Some grade/high school ☐2 Completed high school or GED ☐3 Some college/technical school ☐4 Bachelor's degree(s) ☐5 Graduate degree(s) (e.g. MS, PhD, MBA) ☐6 Professional degree(s) (e.g. JD, MD, DDS)

20. What is your ***gender*** identity?

☐1 Male ☐2 Female ☐3 Prefer to self-describe

21. Are you Hispanic or Latino/a?

☐1 Yes ☐2 No

22. How would you describe your ***race***? Please check ALL that apply to you.

☐1 Asian or Pacific Islander ☐2 Black/African American

☐3 Native American ☐4 White/Caucasian

☐5 Other (please specify) ___________________________________

23. What is the 5-digit ***zip code*** for your residence (i.e.the place where you live most of the time throughout the year)? (e.g. 30322) __________________________________

24. What is your **current** employment situation? Please check ALL that apply.

☐1 I am a full-time student ☐2 I am a part-time student ☐3 I work full-time

☐4 I work part-time ☐5 I am retired ☐6 I am a homemaker/unpaid caregiver

☐7 I do not work ☐8 Other ________________________

25. Has your **employment situation changed** since May 2021?

☐1 No, my employment situation has not changed since May 2021.

☐2 Yes, my employment situation has changed since May 2021

25b. If you answered "Yes" to question 25, what was your **employment situation** before it changed? Please check **ALL** that apply.

☐1 I was a full-time student ☐2 I was a part-time student ☐3 I worked full-time

☐4 I worked part-time ☐5 I was retired ☐6 I was a homemaker/unpaid caregiver

☐7 I did not work ☐8 Other ________________________

26. Please check the category that contains your approximate 2019 annual ***household income*** before taxes. By “household” we mean “people who live together and share at least some financial resources” (housemates/roommates are usually not considered members of the same household).

☐1 Less than $25,000 ☐2 $25,000 to $49,99 ☐3 $50,000 to $74,999

☐4 $75,000 to $99,999 ☐5 $100,000 to $149,999 ☐6 $150,000 or more

A future research effort related to this study will involve **paid focus group discussions** that dive deeper into how vehicle design and driver practices impact comfort while using shared transportation services.

27. If you are interested in participating in a focus group for monetary compensation, please enter the best email address and phone number where we can reach you.

a. Email Address ____

b. Phone Number ____

Thank you again for taking the time to complete our survey!

We appreciate your dedication and time to this project. If you have any additional questions, please contact our research team at survey@ce.gatech.edu.

28. If you have any comments or questions you'd like to leave us about the survey or related topics, please do so below.

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