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Examining the Impact of Stress and Fear of COVID-19 on Transit Travel

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16. Abstract

The COVID-19 pandemic initially caused a significant decrease in travel. Whereas highway travel rebounded quickly, transit use has not fully returned and may not fully return in the short or medium term. This report discusses the results from a survey of travelers' stated use of transit before, during, and after the pandemic, focusing on identifying factors associated with the change in transit use, including stress and fear of COVID-19. The study included data collection in three experiment phases. In the first phase of data collection, the survey was distributed via several online platforms while the data for the second phase of the experiment was collected at Texas A&M's Human Behavior Laboratory (HBL). The third phase included a virtual reality (VR) experiment conducted at the University of Puerto Rico at Mayagüez that included skin conductance response measurements along with the survey questionnaire.

The research found there may be as many as 35% to 45% of respondents who will not use transit as much in the future due to COVID-19. This higher range occurs if both the responses "Extremely" and "Very" are considered indicators of future travel decisions for survey questions asking the importance or likeliness of COVID-19 factors. However, if we consider only those respondents who indicated "Extremely Important," "Extremely Likely," and "Extremely Uncomfortable," then a lower range of 15% to 25% of respondents will not use transit as much in the future. When examining Texas A&M students only, the percentage who may use less transit due to COVID-19 is likely smaller than 15%, but greater than 0%. Therefore, in addition to telecommuting and mode shifts caused by the pandemic, transit agencies must overcome the stresses and fears that commuters have related to COVID-19 for ridership to return to pre-pandemic levels.

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Executive Summary

The COVID-19 pandemic altered daily life by forcing governments to issue measures for the prevention of the spread of the disease such as stay-at-home orders, requiring face coverings, and maintaining physical distancing, among others. This caused a significant disruption in every aspect of people's lives. This disruption was prominent in the transportation sector where travel decreased drastically. Although highway travel rebounded quickly as businesses, retail, services, and other workplaces and services returned to in-person activities, the much slower rebound of transit ridership raises a concern that transit users might not fully return in the short or medium term. This may cause increased congestion, particularly in cities where many commuters rely on transit travel. Beyond the impact of significant telework, one reason for this drop in ridership may be an individual's psychological factors like stress/fear of catching a virus in mass transportation systems like transit. These factors could play a major role in predicting the future use of transit.

This research examines the results from a survey of travelers' stated use of transit before, during, and after the pandemic, focusing on identifying factors associated with the change in transit use, including survey instruments to assess the stress and fear of COVID-19. Traveler's stress levels during the survey were also measured using Galvanic Skin Response (GSR) and facial expression, along with self-reported levels of stress. This may provide additional insight into the reasons why many travelers have not returned to transit. An additional effort included a virtual reality (VR) experiment with skin conductance response (SCR) measurements and the survey questionnaire that could immerse subjects in a typical transit situation and that could provoke a reaction of risk related to COVID-19 that could be used to record peaks in the stress levels of the persons.

The results from the survey of travelers found that approximately 41% of respondents reduced their use of transit after the pandemic declaration in March 2020 and 45.5% stated they were less willing to use transit in the future even after the pandemic is over. Respondents who stated a lower use of transit during the pandemic also had higher average stress levels and higher fear of COVID-19. A Random Forest Classification Model and a SHAP Value Plot were used to identify factors relevant to the stated reduced transit use for those travelers that were frequent transit users before the pandemic. Household size and annual income, the comfort level of a person when faced with a crowded bus, the fear or risk of contracting COVID-19, working from home, along with age and gender characteristics, were among the key factors associated with the stated reduction in transit use.

In the second phase of the study, a nearly identical survey was conducted in the human behavior laboratory (HBL) at Texas A&M University where respondent stress levels were measured while taking the survey. The findings from the second phase revealed that almost half of the respondents, 46%, decreased their use of public transportation after the pandemic was declared in March 2020 and nearly a quarter, 22.5%, stated they would use transit less even after the pandemic ends. Analyzing the peak stress events, it was found that both the first-perspective videos of a crowded bus stop and a crowded bus ride caused stress in a majority of participants. However, there were four questions that participants were asked about these videos and answering them correctly would increase their payment for taking the survey by $1. Participants were also stressed about these questions which means their stress measured while watching the video could have been due to the extra compensation. Respondents who did not show any stress were more likely to not change their transit use. Also, participants who indicated stress while answering the question regarding the reasons that prevented them from using the bus often were 11% more likely to indicate they intended to decrease their future transit ridership.

Note that all these results are based on respondents stated preferences in the summer of 2022. There could easily be considerable changes over time depending on many factors, including vaccine efficacy and new COVID-19 variants.

The third experiment phase was effective to demonstrate that the virtual reality (VR) simulation technology was an effective tool to immerse people in a typical transit scene, such as waiting for a bus and riding inside a crowded bus, while recording their stress levels. The VR experiment treatments were based on two sizes of crowding and the presence of coughing, two main COVID-19 exposure factors. Seeing large groups of persons gathering at a stop waiting for a bus and having to share the confined space inside the bus with a large group of transit riders, in addition to the presence of coughing, was found to be significant on the stress levels of the subjects. The results from a Poisson model confirmed that observing and hearing nearby avatars coughing at the stop and inside the bus was the most significant factor for the recorded peaks in the stress level of subjects.

The research found there may be as many as 35% to 45% of respondents who will not use transit as much in the future due to COVID-19. This higher range occurs if both the responses “Extremely” and “Very” are considered indicators of future travel decisions for survey questions asking the importance or likeliness of COVID-19 factors in determining that respondents future transit use. However, if we consider only those respondents who indicated “Extremely Important,” “Extremely Likely,” and “Extremely uncomfortable,” then a lower range of approximately 15% to 25% of the respondents will not use transit as much in the future due to COVID-19. When examining Texas A&M students only, the percentage who may use less transit due to COVID-19 is likely smaller than 15%, but greater than 0%. So, even amongst this group, COVID-19 has a negative impact on transit use. Therefore, in addition to substantial telecommuting and mode shifts caused by the pandemic, transit agencies must overcome the stresses and fears that the commuters have related to COVID-19 for ridership to return to pre-pandemic levels.

Chapter 1. Introduction

The World Health Organization (WHO) declared COVID-19 a global pandemic in March 2020 (Cucinotta and Vanelli, 2020). High transmissibility, lack of treatment, and fatality rates made this disease a global public health emergency (Liu et al., 2020). The pandemic not only challenged health systems all over the globe but also forced governing authorities to take precautionary measures to stop the spread of the virus. These measures included stay-at-home orders, shutdown or reduced operations of transit services, mandatory face covering, and social distancing, which minimized human mobility and reduced travel demand (Mervosh et al., 2020). With the onset of COVID-19, every aspect of our daily lives changed. The impacts in transportation included a significant decrease in all trips on toll and managed lanes facilities and transit ridership. Travel in general, and even on toll facilities, rebounded just months after the emergency declaration in March 2020, but transit travel has not. In addition to the fear of COVID-19, transit has also suffered from a shortage of drivers, capacity reductions, changes in operation hours, and even service suspensions, motivating users to shift to other travel modes. With the shift toward working from home, there is concern that transit ridership might not fully rebound to pre–COVID-19 levels or might require major interventions. These changes in travel could result in additional congestion and emissions in dense urban areas that have traditionally relied on transit.

Transit agencies responded to the challenges imposed by the pandemic by establishing cleaning protocols, mask offerings, grocery shopping pick up services, eliminating fare payments, among other strategies to increase ridership (Mader, 2021). The search for strategies to recover transit ridership includes investigating travel demand shifts and pursuing innovation in how transit will provide services in the future. As part of this effort, it is essential to understand the role COVID-19 plays in the reluctance of some travelers to return to transit.

While there have been several studies that have explored post-pandemic traveler decision-making using survey responses, the existence of psychological scales in a survey to improve our understanding of travel behavior has not been adequately explored. The objective of this research was to understand if and how psychology/stress may play an important role in travel behavior, especially transit use and how fear of COVID-19 may impact transit use. Galvanic Skin Response (GSR) equipment was used to measure the neurophysiological state in combination with a survey instrument to better understand the human behavior involved in decision-making while making revealed or stated travel choices in a realistic travel environment.

This report presents the results of the study that examined the traveler's stated use of transit before, during and after the pandemic with a focus on how the traveler's stress level and fear of COVID-19 impacts their transit use. Interviews with transit owners and operators and a survey of 6,300 travelers were examined in the first phase of the research. The Texas A&M team conducted a computer-based survey along with the GSR instrument to examine nearly 200 travelers in the second phase of the research. The UPRM team conducted the VR experiment along with GSR measurements to examine the response from 32 subjects. The GSR measurements, in combination with the survey and the VR simulation, were used to better understand the human behavior involved in decision-making while making revealed or stated travel choices in a realistic travel environment. The hypothesis under study is that future travel, especially in a shared mode like transit, has a lot to do with the person's fear of COVID-19 and psychological makeup. Thus, these personality traits would be helpful in predicting the fear and estimating the likelihood of a person's use of or return to transit. These findings will therefore be useful in improving transportation planning.

Chapter 2. Methodology

This chapter briefly outlines how the research proceeded. First, researchers examined previous literature and surveys from around the world to examine behavioral change in travel due to the COVID-19 pandemic and other major shocks to travel. Researchers also examined travel data from various data sources to understand travel trends before and after the pandemic. This provided critical background information but also found gaps in prior research which were the focus of this study. Then, researchers interviewed transportation experts to better understand the challenges faced during the start of the pandemic, as well as the current challenges, and how those are different from past challenges. A survey instrument was developed and administered to travelers with a focus on their change in transit usage. The survey responses were analyzed in conjunction with their stress levels and fear of COVID-19 to gain a better understanding of their potential return to transit usage.

In the second phase of the research, researchers at Texas A&M invited student subjects to take the survey at the Human Behavior Lab (HBL) on the Texas A&M campus. Here the subjects took the survey while connected to GSR and their facial expressions were observed. This provided additional information regarding the stress felt by participants when answering transit and COVID-19 related questions.

Researchers at UPRM conducted an experiment using Virtual Reality (VR) technology in combination with the survey instrument and the GSR equipment. The experiment immersed subjects in a simulation of a city street that required them to interact with avatars of persons waiting at a stop shelter and then inside a bus with passengers. The objective of the VR experiment was to recreate typical situations people face when using transit to study if the scene provokes a reaction based on COVID-19 exposure factors embedded in the simulation. The electrodermal activity (EDA) or skin conductance response (SCR) of the subjects was registered with the GSR instrument and analyzed to study if there was a relation between the reactions of the subjects in the VR experiment and the COVID-19 factors.

The explanation of the processes and methods followed to conduct the different phases in this study is provided in the corresponding chapters of this report. The report presents the findings from these efforts.

Chapter 3. Literature Review

The COVID-19 pandemic affected every aspect of daily lives, including travel. Lockdowns, physical distancing, and mask mandates resulted in a significant decrease in transit travel. Increased teleworking, distance learning, and online shopping bolstered the impact of the pandemic and further reduced travel. Though these regulations were used to safeguard people's health from the virus, they had a significant impact on people's views about the risk associated with this virus. With reemerging waves and COVID-19 variants, the pandemic appears to extend its impact on travel choices.

Large Scale Change in Travel

The vehicle miles traveled (VMT) in the United States (U.S.) dropped by 10% in a year-over-year change through August (BTS, 2022). The drop in VMT due to the COVID-19 lockdown was nearly 36% in April 2020, when compared to a January 2020 baseline (see Figure 1). Figure 1 depicts how highway VMT in the U.S. rebounded quickly from the first abrupt decline at the time of the pandemic emergency declaration in April 2020, reaching pre–COVID-19 levels as soon as July 2020. Highway travel experienced a second abrupt reduction of 21% in January 2021 as the daily number of COVID-19 related deaths in the U.S. reached its highest point during the pandemic (Dong et al., 2023). Highway VMT recovered again quickly in March 2021 and maintained a similar pre-pandemic trend up to March 2023 as demonstrated by the data published by the BTS (2023).

Nationally, transit ridership dropped by nearly 80% in April 2020 and remained low for the rest of 2020 as compared to 2019 (APTA, 2021). The decrease in ridership was nearly 1.3 times higher for rail services (commuter and subway) as compared to bus services (APTA, 2021). Ridership of Metrorail in Washington, D.C. plummeted by 90%, and the bus ridership declined by 75% at the end of March 2020 (WMATA, 2020). Heavy rail and bus services in the San Juan Metropolitan Area (SJMA) in Puerto Rico were shut down for six months after the pandemic declaration. The Tren Urbano heavy rail in the SJMA had a 77% decrease in ridership when comparing the months of February 2020 and February 2021. Revenue losses and increasing cleaning costs forced transit services to limit their operations, which meant overcrowded passenger space and therefore potential increased transmission (Garza, 2020; De Vos, 2020; DeWeese et al., 2020; Hu and Chen, 2021). The rebound of transit ridership is nowhere near pre-pandemic levels which is concerning as it may lead to additional congestion in dense urban areas relying on transit. It is likely that some of the transit riders shifted to private vehicles, which might have helped in the swift rebound of highway travel and VMT. The transit travel risk perception among people may be prolonged with reemerging waves and new COVID-19 variants.

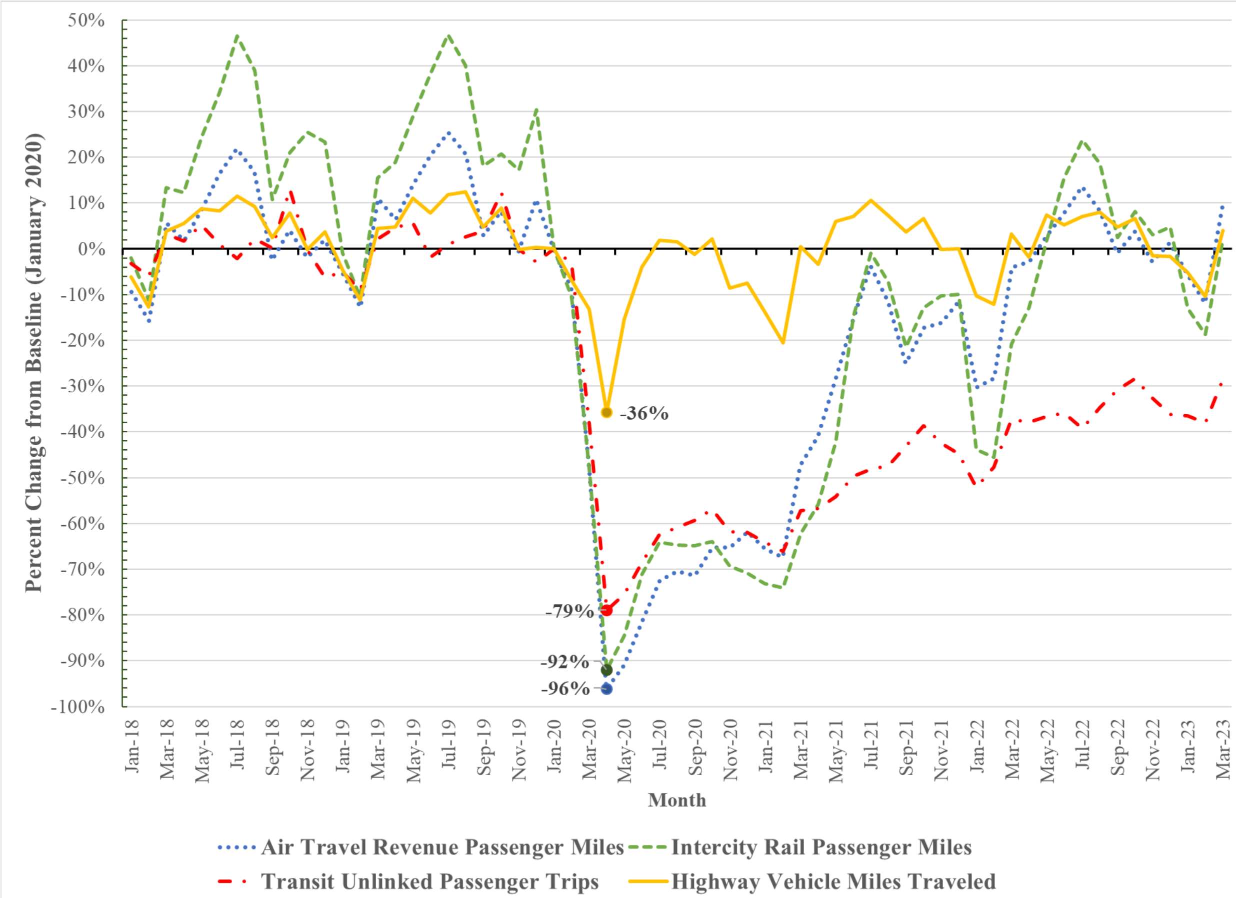


Figure 1. Impact of COVID-19 on Travel by Mode
(Source: https://data.bts.gov/stories/s/m9eb-yevh#system-use)

The impact of COVID-19 was not only limited to roads and transit. Air and intercity rail travel in the U.S. recorded substantial reductions of 96 and 92%, respectively, in passenger miles (PM) at the onset of the pandemic emergency in April 2020. The U.S. air industry recorded cancellations of 43 and 38% of the flights scheduled for March 26 and April 2, 2020, respectively, representing a total of 4.4 million less passengers when compared with the same dates on 2019 (Nguyen and Animashaun, 2020). Despite these extreme reductions, both travel modes have recovered PM reaching pre-pandemic levels by July 2021 (briefly) and then again in May 2022.

Bike-share and e-scooter ridership saw a dramatic decrease in ridership with a year-over-year decline in docked bike-share trips for the six largest systems by as low as 65% in April 2020 as shown in Figure 2. This resulted in the permanent closing of 35 bike-share and e-scooter systems and suspending operations of as many as 156 systems by the end of August 2020 (Bureau of Transportation Statistics, 2021).

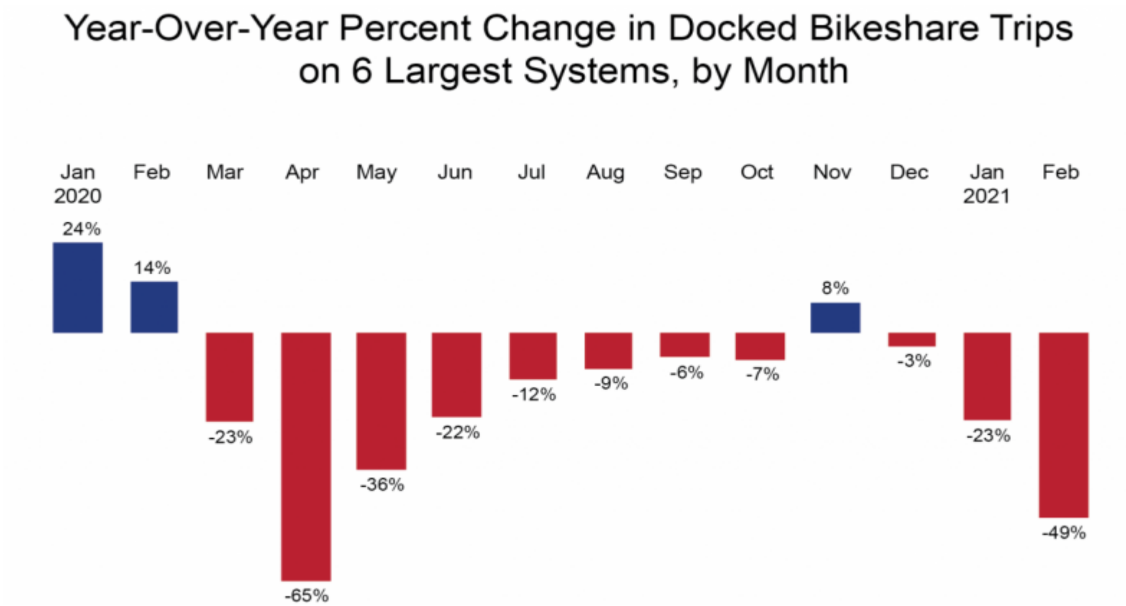


Figure 2. Impact of COVID-19 on Bikeshare Systems
(Source: https://www.bts.gov/data-spotlight/covid-19-crushes-bikeshare-e-scooter-ridership)

A research study found that 44% of professionals in the Netherlands started working from home, and about 80% of people reduced outside activities. Compared to previous years, the number of trips and distance traveled dropped by 55% and 68%, respectively (De Haas et al., 2020). Considering the statistics at the start of the pandemic, there was a general fear that transit ridership and toll road traffic might not rebound fully to pre–COVID-19 levels.

Change in Toll Road Use

Toll roads were greatly affected by the pandemic with the monthly transaction index showing an average drop of 54% in toll revenue collection of agencies with centerline miles greater than 150 in the month of April 2020 (see Figure 3) based on the data collected by CDM Smith (Prezi, 2021). With the significant shift toward working from home at the start of the pandemic, the general opinion was that toll roads/managed lanes may not rebound due to less congested toll-free alternatives, causing revenue loss. Figure 3 represents the toll road index that depicts the performance of toll roads compared to previous year. An index of 1 illustrates no change in performance whereas an index of 1.1 depicts a 10% increase in performance. The data reveals that the index rebounded quickly after April 2020 and showed positive revival signs as of December 2020 with an average 19% decrease in performance compared to 54% decrease in April. The analysis was done by comparing the monthly toll road traffic and revenue of some of the states, as shown in Figures 4, 5, and 6, revealing that traffic on toll roads have almost rebounded to pre–COVID-19 levels. Fitch Ratings (October 2022) monitors the health of toll road investments and found toll road traffic essentially to be equal to pre-pandemic levels as of October 2022. In some states, such as Texas and Florida, toll road traffic has exceeded pre-pandemic levels.

The past literature and latest trends show that although road and toll travel was affected significantly by COVID-19, it has shown positive signs of bouncing back to pre-pandemic levels.

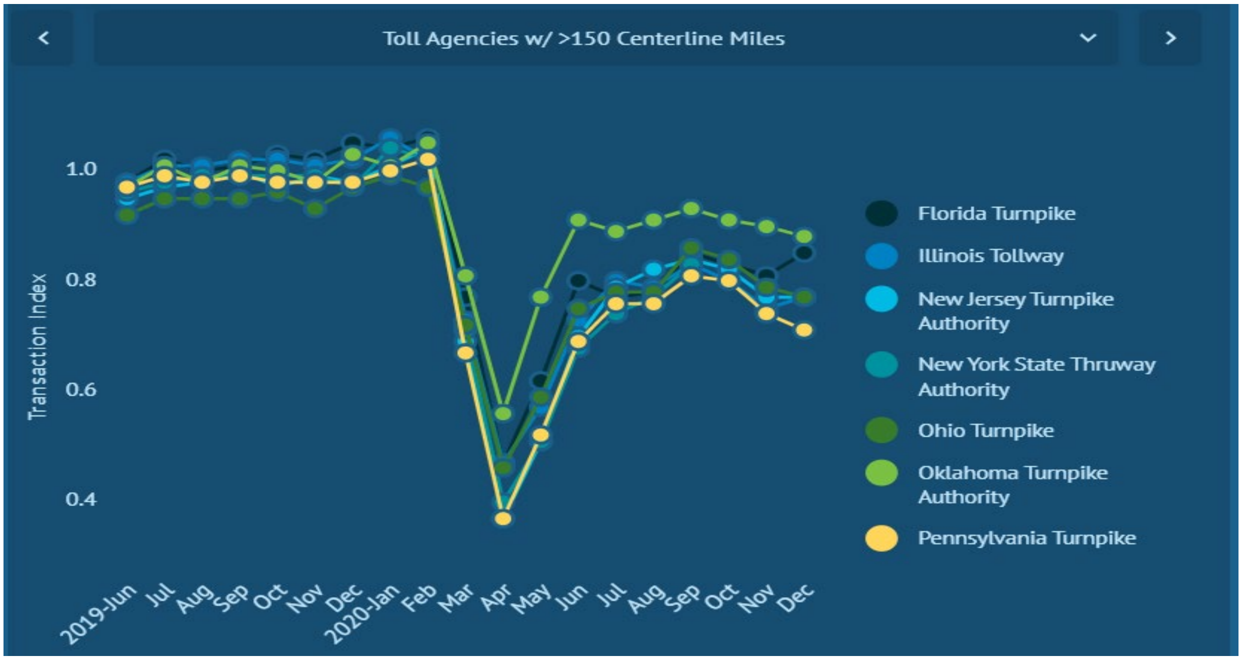


Figure 3. Impact of COVID-19 on Toll Roads – Monthly Transaction Performance (Source: https://prezi.com/i/ap5to7mq2yim/2021-q1_tolling-industry-times_stats/)

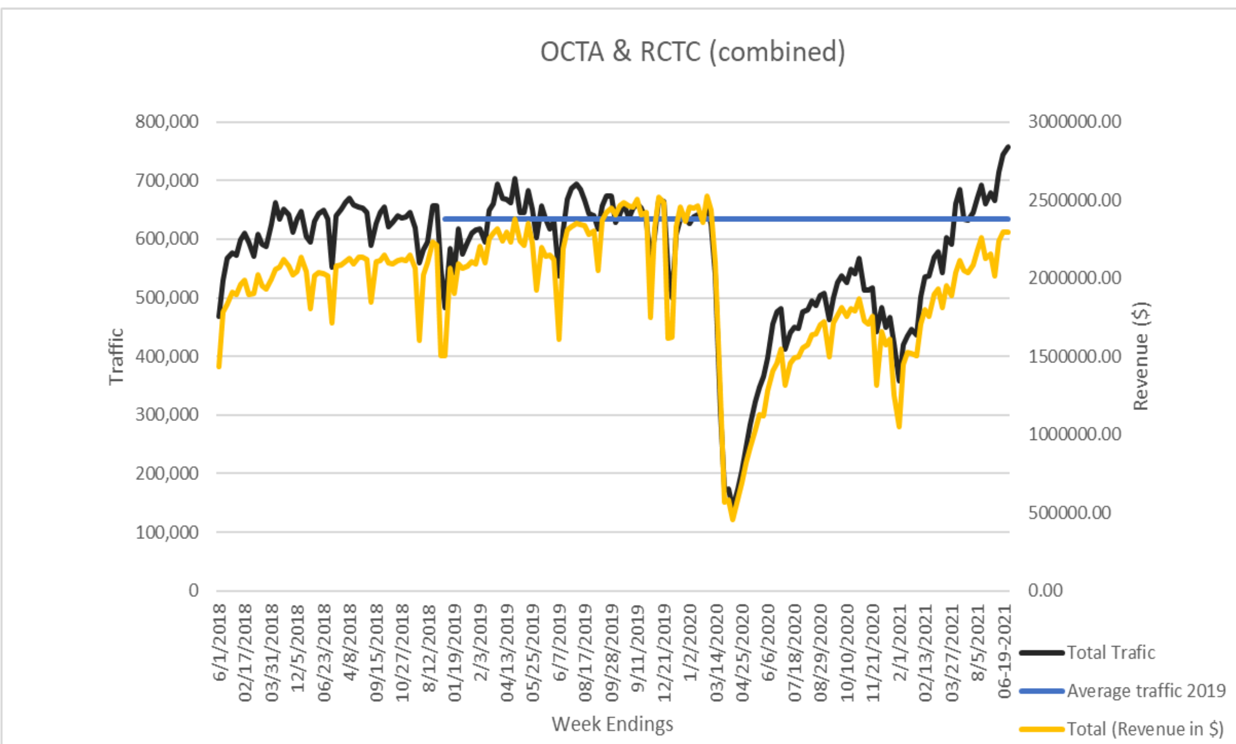


Figure 4. Weekly Traffic and Revenue Analysis of 91 Express Lanes, California

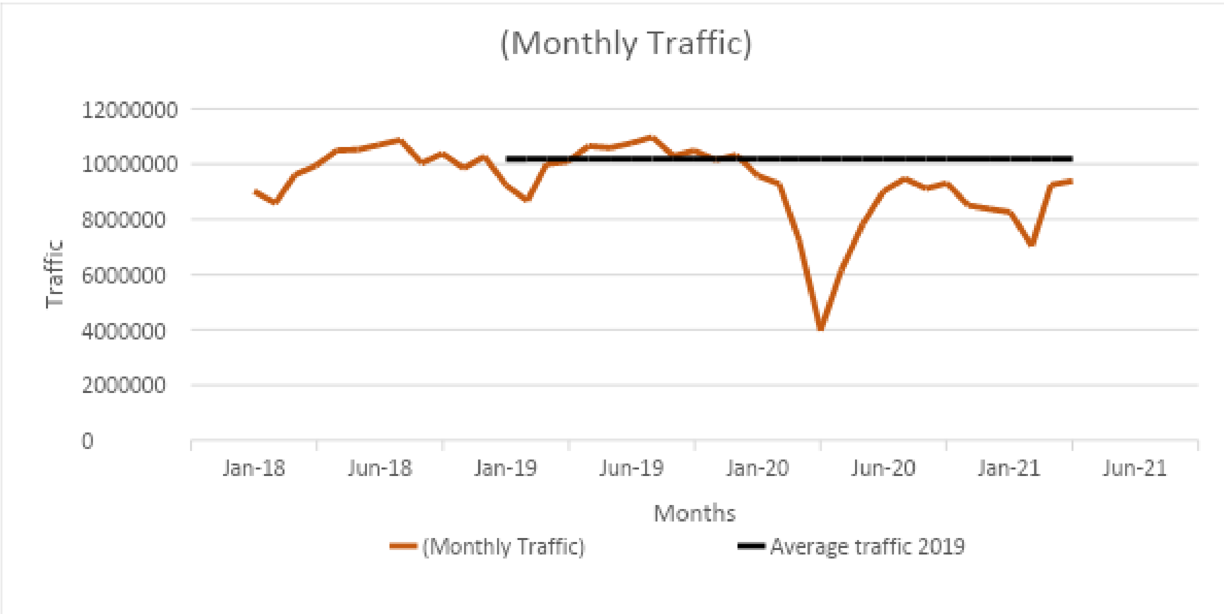


Figure 5. Monthly Traffic Analysis of the Port Authority of New York and New Jersey

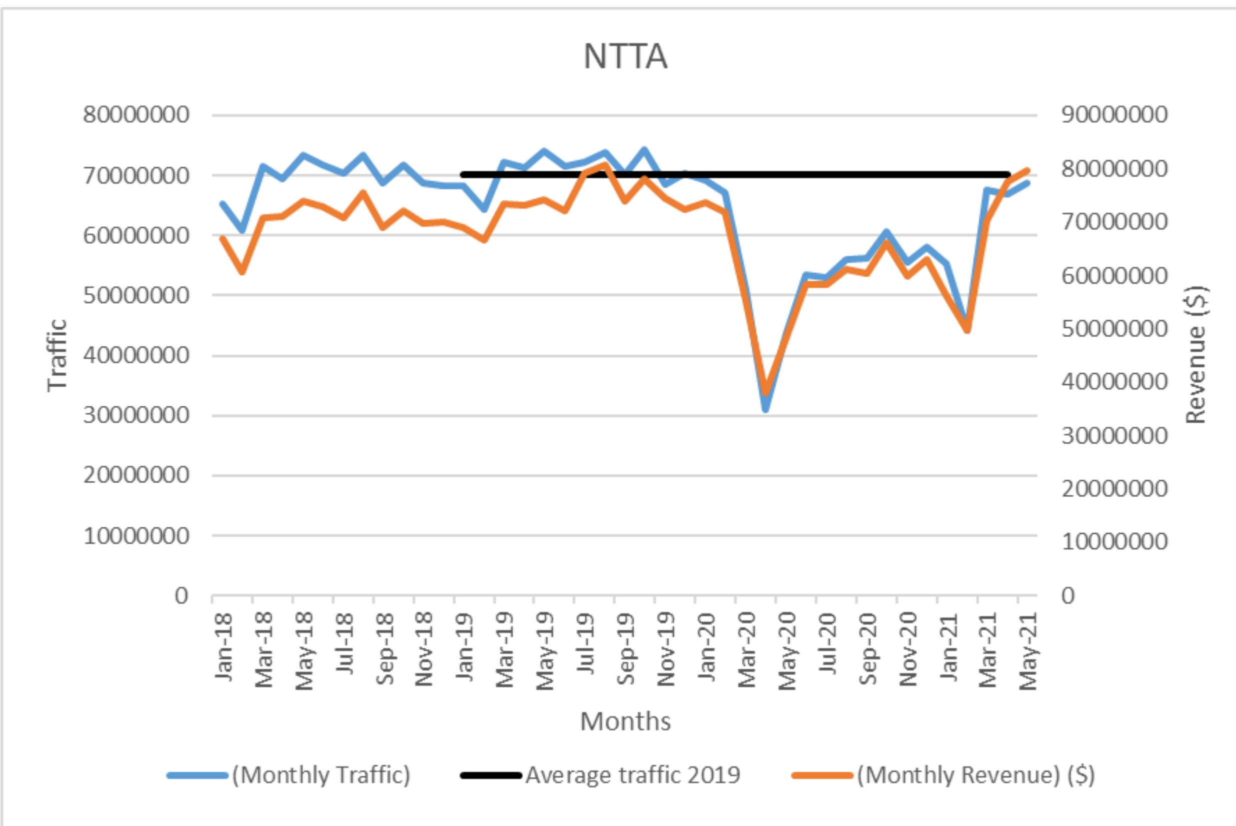


Figure 6. Monthly Traffic and Revenue Analysis of North Texas Toll Roads

Comparison to Previous Shocks to the Transportation System

The worldwide outbreak of COVID-19 was an unprecedented shock event in the transportation sector. Ascertaining how long the impact may last is important to the prediction of travel in the post-pandemic era and a challenging task. The economic recession in 2008 significantly impacted freight transport due to its correlation with trade, but the impact of the recession on domestic passenger transport was relatively small and short lived. The impact of several economic recessions dropped the nation's miles traveled but those impacts were very small compared to COVID-19's impact (see Figure 7).

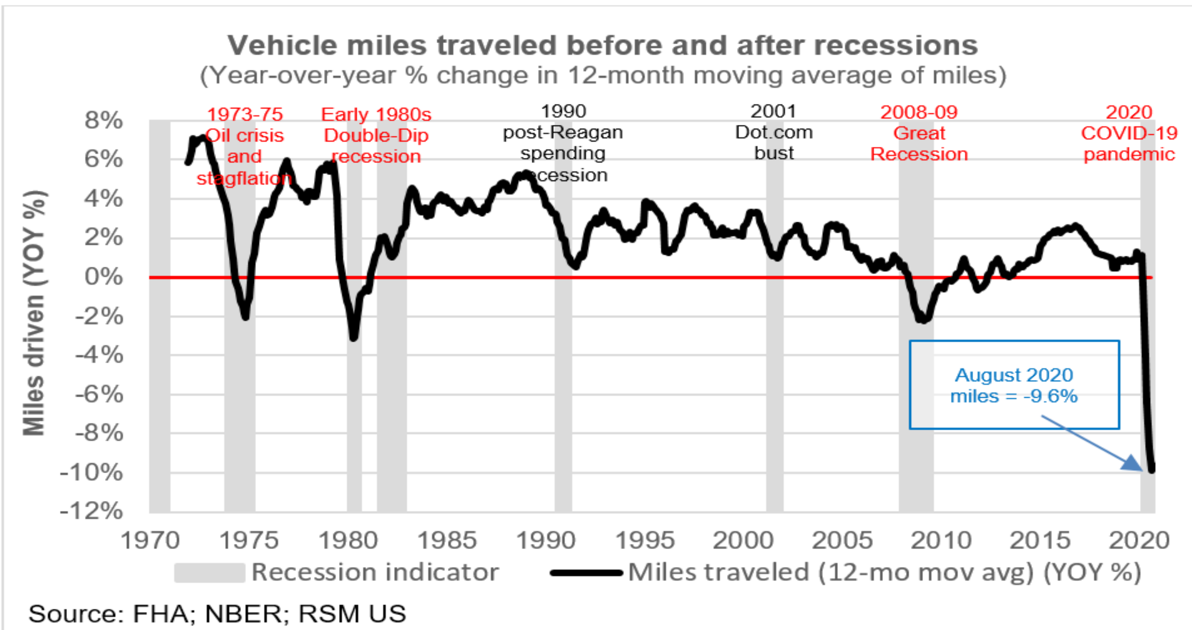


Figure 7. Vehicle Miles Travelled Before and After Recessions
(Source: https://realeconomy.rsmus.com/a-recession-like-no-other-total-vehicle-miles-traveled-plummets-to-record-lows/)

The upsurge in oil prices during 1973 due to the Oil Crisis, in 1978–1980 due to the Iranian Revolution, and in 2008 due to the recession were minor shocks with short-term impacts on VMT in the U.S. (see Figure 8). The 9/11 attacks and the 2004 Madrid and 2005 London bombings posed local security threats that resulted in a reduction in transit travel. These disruptions due to terror attacks share some likeness with the current pandemic as people avoided transit in fear of subsequent attacks. The underground passengers in London fell by 8.3% for four months after the 2005 attack (Prager et al., 2011). However, passenger volume returned to normal a year later. The shock to the transportation sector from COVID-19 is unlike anything recent generations have experienced and therefore examining past results in hopes of predicting how travel will rebound after this pandemic might not be accurate.

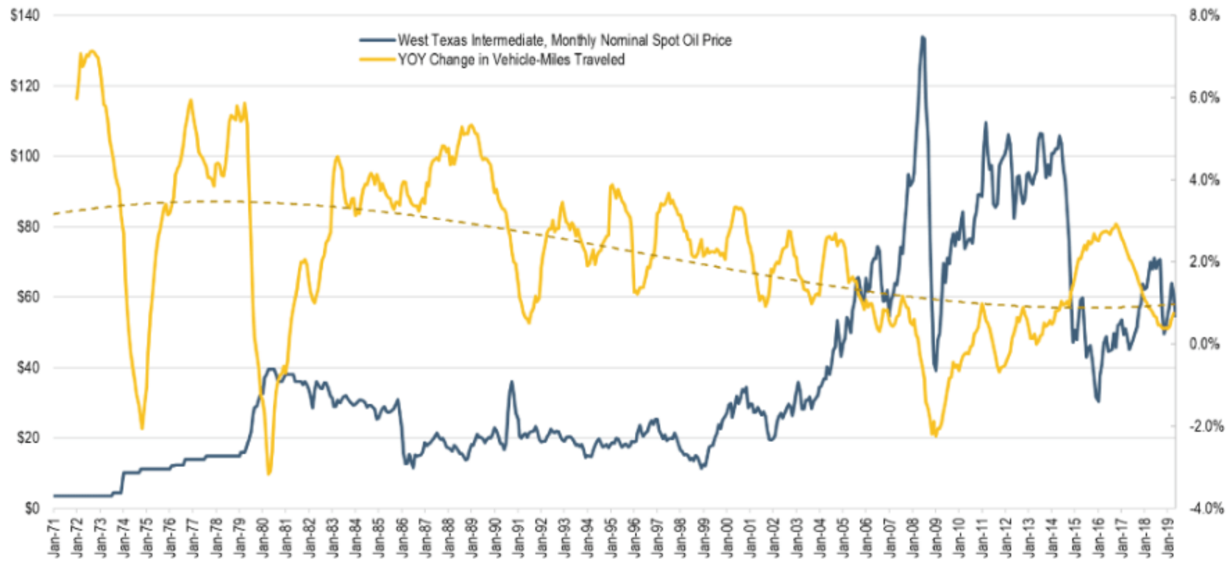


Figure 8. Oil Crisis Impact on Vehicle Miles Travelled
(Source: https://transportgeography.org/contents/chapter4/transportation-and-energy/vehicle-miles-united-states/)

The world has experienced several diseases before COVID-19, such as SARS and H1N1, which restricted international air travel and tourism to the affected countries. A survey explored the level of concern and precaution among Australians to the H1N1 pandemic. It showed that even with most people concerned about the virus, many of them were not willing to delay their travel plans despite exhibiting any similar symptoms indicative of the H1N1 pandemic (Leggat et al., 2010). The Health Belief Model studied the factors influencing the domestic travel avoidance by US citizens during the EBOLA outbreak and predicted that people with higher risk perception, perceived susceptibility, and subjective knowledge were inclined to avoid domestic travel (Cahayento et al., 2016). Researchers examining the MERS outbreak in South Korea explained the effect of fear of infection on travel behavior, especially for transit, with its influence depending on demographics characteristics and the extent of infection in that area (Kim et al., 2017). The SARS outbreak in Taipei showed both the fresh fear and residual fear among the passengers. The fresh fear showed an immediate loss of 1,200 riders with each increase in the case of virus. Transit did not return to pre-SARS level until approximately 5 months after the last related death, showing the residual fear of virus among the passengers (Kuo-Ying Wang, 2014). These other diseases, being transient and less severe than COVID-19, disrupted transit and highway VMTs for a shorter duration and had a short-term impact on travel. Predicting how transit ridership may or may not rebound from COVID-19, based on the experience from these other pandemics, might prove to be inadequate.

The COVID-19 pandemic has caused a significant disruption in travel behavior. To study this disruption many surveys and studies examining its impact have been conducted. A study evaluated how government mandates and local infection familiarity affected individual mobility at county level. It found that stay-at-home orders reduced the individual mobility by 7.87% and with a marginal increase in local infection from 0% to 0.003%, the mobility reduced by 2.31% (Engle et al., 2020). A survey conducted by Transport Scotland (2021) found that almost half of respondents (46%) avoided transit and used their cars more than they did before the pandemic. Similarly, a UK survey (2021) found that a third of respondents stated to continue to drive more and use transit less even when COVID-19 no longer poses a significant risk. Australians showed a notable increase in their intentions to use cars and a decrease in intentions of using public transit even after the removal of restrictions (Thomas et al., 2021).

Another survey from Scotland stated that 36% of respondents anticipated using buses less and 34% anticipated using trains less after the pandemic (Downey et al., 2021). A nationwide online survey study conducted in the US discovered that those with access to a private motor vehicle were more likely to lessen or cease using public transportation compared to those without access (He et al., 2022). According to a survey conducted in Japan, 36% of the respondents modified their travel habits and used less public transportation (Zhang, 2021). Over 50% of respondents without automobiles wanted to buy one after the pandemic, while about 40% of transit users in China said they switched to motor vehicles (Zhou et al., 2020). A survey done in the United Kingdom (UK) found that 20% of the regular transit riders prior to the pandemic were no longer willing to use public transportation (Harrington and Hadjiconstantinou, 2022). Passengers aged 65 years and above reduced their subway rides more compared to passengers aged between 20 and 64 years (Park and Cho, 2021). These results showed the elderly's sensitivity toward the risk of the pandemic was likely to be stronger, leading to a greater avoidance of public transportation.

A research study found that the major shift in mode choice from public transportation to private vehicles was due to respondents prioritizing the infection-related factors more than travel time savings and cost of travel (Abdullah et al., 2020). The results also indicated that the primary trip purpose for commuters before COVID-19 was work (58%) which changed to shopping (40%) during COVID-19. The behavior changes and the impacts from the pandemic varied among socioeconomic groups. The impact inference model quantitatively confirmed that less educated, lower-income, and people of color are more likely to ride transit during COVID-19 (Hu and Chen, 2021). Transit ridership fell between 30 to 40 % in Santiago among low-income households compared to a drop greater than 70% among high-income households (Tirachini and Cats, 2020). Luyu Liu et al. (2020) modeled the decline in daily demand for U.S. public transit systems. The study revealed that communities dominated by a larger proportion of essential workers, vulnerable populations such as Hispanics, females and individuals aged above 45 years, as well as those with more Google searches related to "coronavirus" had a smaller decline in demand compared to other communities. The results also indicated that the demand difference between weekdays and weekends became less obvious during the pandemic as compared to normal days. Compared to pre-pandemic levels, a survey study in Melbourne found that transit travel was reduced by 6% during peak periods and expected a reduction of 20% to the downtown commute post-pandemic (Currie et al., 2021). The major reason for this stated behavior change was the increase in work from home. The study estimates the car commute will increase by 5% post-pandemic. These studies clearly show a shift away from transit which might have resulted in speeding up the rebound in road travel.

Stress and Fear of COVID-19

It is anticipated that COVID-19 will have a significant physiological impact on individuals. Thus, this impact needs to be considered while assessing travel in transit as it is anticipated that future travel decisions, especially in a shared mode like transit, will have a lot to do with the person's feelings and psychological makeup.

Ahorsu et al. (2020) developed and validated the Fear of COVID-19 Scale (FCV-19S) as a seven-item questionnaire to quantify the psychological fear of COVID-19 among individuals. Bitan et al. (2020)

concluded the FCV-19S could be utilized to find the impact of the pandemic on the public's mental health. A survey conducted in India used this scale and found that females, married people, and less educated people had a greater fear of COVID-19 (Doshi et al., 2021). Several research studies have verified FCV-19S worldwide and discovered various applications from its use. Therefore, the FCV-19S instrument was included as part of the survey conducted in this study to assess people's fear of COVID-19. Appendix A shows the survey questionnaire used in the present study with the FCV-19S instrument included as questions 5.1 to 5.7.

The Perceived Stress Scale (PSS) is a psychological tool developed in 1983 by Cohen et al. to find the respondent's level of perceived stress. This instrument has been used to find the degree of stress caused in one's life in different situations. A correlation of the PSS with health measures has been found associating higher scores with depression, failure to quit smoking, etc. (Cohen et al., 1983). With translation into numerous languages and validation in multiple countries, this tool has been effective in judging the stress of an individual. There has been no literature studying the interrelation of these scales with travel behavior, especially shared modes like transit. The PSS questions were also incorporated as questions 4.1 to 4.10 of the survey questionnaire used in the present study (shown in Appendix A).

Chapter 4. Background Information

The impacts of the COVID-19 pandemic were rapidly changing as this present study was being conducted, so it was important to seek additional insight and up to date data to expand the information found in the literature. Recent transit ridership and highway VMT data available from several states and Puerto Rico was analyzed, and conversations and focal groups with transportation experts were conducted to acquire relevant and pertinent information about the impacts and strategies for COVID-19. The results from these efforts are discussed in this chapter.

VMT Rebound for States that Quickly and Slowly Reopened

The nation observed a steep decrease in VMT at the initial stages of the COVID-19 emergency declaration, as shown in Figure 1. The shift to teleworking and remote education modes, the enactment of restrictive government policies to control the spread of the disease, and the fear of getting infected among the public, raised a general concern that road travel might not rebound fully. The latest trend shown by the U.S Department of Transportation revealed that the national impact of COVID-19 on VMT was short-lived, showing a rather fast rebound.

To analyze the impact on different states of the pandemic and the government policies, VMT from eight states, that represent around half the U.S. population, were examined. The eight states selected were categorized into two groups based on the speed of reopening businesses and softening of mobility restrictions. Texas, Florida, Georgia, and North Carolina were some of the larger states that reopened quickly. In contrast, California, Illinois, New Jersey, and Virginia were some of the larger states that reopened slowly. Vehicle miles traveled (VMT) data from the official site of the U.S Department of Transportation was used to analyze the rebound and assess the impact of reopening policies on travel. The relative VMT for each state was calculated for this purpose. Relative VMT was defined as the ratio of the VMT for each month in 2020 to the average monthly VMT for all of 2019 for a particular state. The Relative VMT signified the extent to which the traffic has rebounded compared to the pre–COVID-19 in the year 2019. Therefore, a value equal to one means that traffic has recovered equivalent to the pre–COVID-19 period, whereas a value < 1 indicates that VMT in 2020 is less than in 2019.

A timeline of orders from each State was noted to assess the impact of reopening policies and phases on the VMT. To keep consistency in the reopening phases, reopening at 25% capacity was considered Phase 1, reopening at the 50% capacity was considered Phase 2, reopening at more than 50% capacity was considered Phase 3, and no restrictions were considered as fully reopened. Although there was no clear indication of the exact timeline for reopening phases 2 and 3 in California, it is generally recognized as one of the slowest reopening states.

Figures 9 and 10 show the Relative VMT per month for the fast- and slow-reopening U.S. States, respectively. A color-coding scheme was used in the data to show the influence of the phased reopening and mandatory orders on travel for each state. For uniformity, the blue color shows pre–COVID-19 months, the black color indicates the period of stay-at-home orders, the orange color indicates Phase 1, the red color indicates Phase 2, the purple color represents Phase 3, and the green color is the full reopening period.

The measures of relative VMT show a reduction in VMT was already happening in the eight States before the U.S. emergency declaration in March 2020. The steep decrease in relative VMT due to stay-at-home orders continued for the two groups until April 2020. The phased reopening showed an increase in VMT, bolstering the theory that the ease in restrictions increased travel. Both North Carolina and California achieved a short-lived full rebound of VMT in October 2020. The Omicron variant of the virus was discovered in November 2021, with the first U.S. cases found one month later (Katella, 2023). The three highest weekly death rates per 100k people in the U.S. so far during the pandemic, from 5.88 to 7.08, were registered in December 2020 and January 2021 (CDC, 2023). With the eight States already at a Phase 3 reopening stage, the relative VMT showed a new decreasing trend in travel, reaching a low point in February 2021 (except California that reached in January 2021). Both groups recovered to an almost full rebound by May 2021.

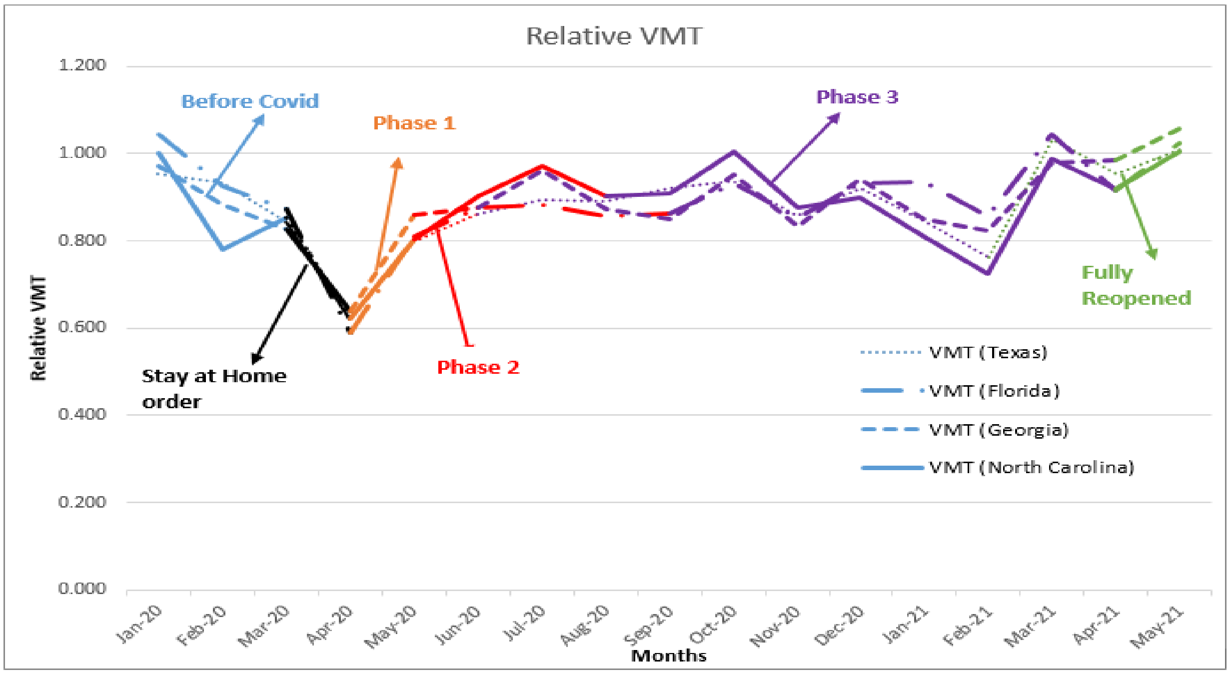


Figure 9. Relative VMT of Fast-Reopening U.S. States

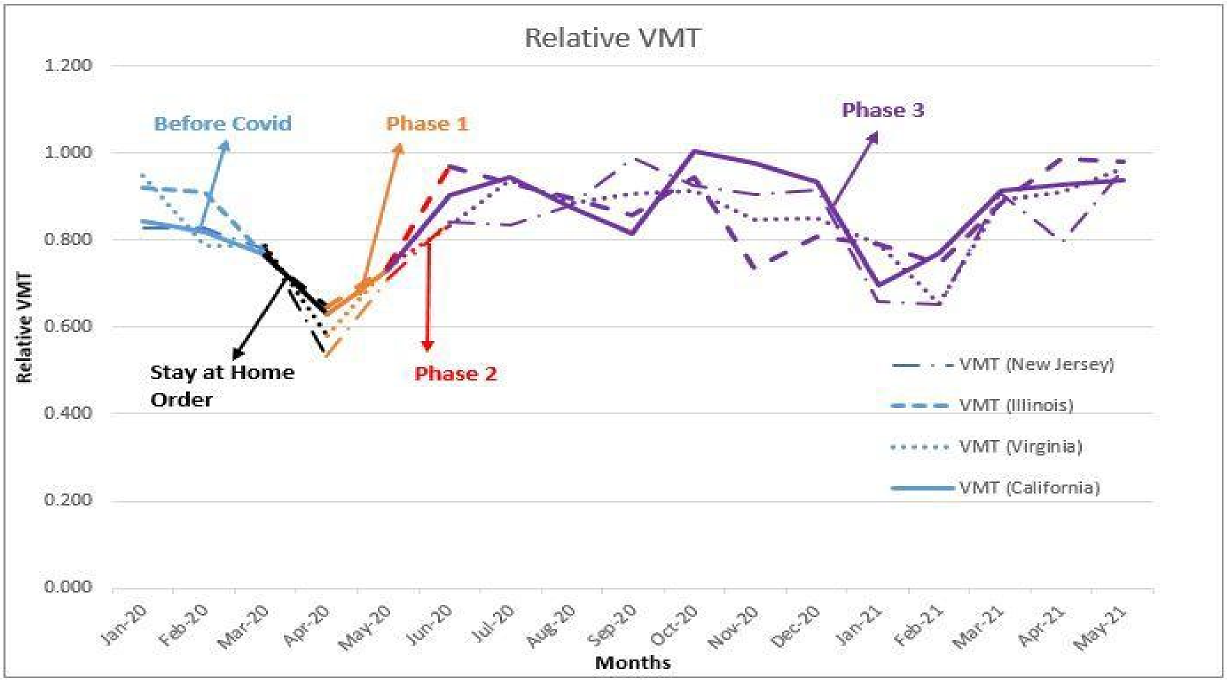


Figure 10. Relative VMT of Slow-Reopening U.S. States

Figure 11 shows the average VMT for both groups. The overall impact of policies is minimal on the Relative VMT as both groups show similar trends. The graphs indicate a slight difference between the two groups with the average Relative VMT for the fast-reopening states reaching a value of one in March 2021 and exceeding it in May 2021, whereas the average behavior for the slow-reopening states does not reach the Relative VMT value of 1. A reason for the slight difference could be there four fast-reopening states fully reopened between April and May 2021 whereas the others did not. This analysis helped to assess that even the most restrictive states showed a full rebound in highway VMT during the period this study was being developed. Policies and reopening phases had an impact, but it appeared to be minimal. The results obtained from the VMT analysis and the promising rebound of VMT observed during the time this study was conducted, the researchers decided to focus on the impact on transit.

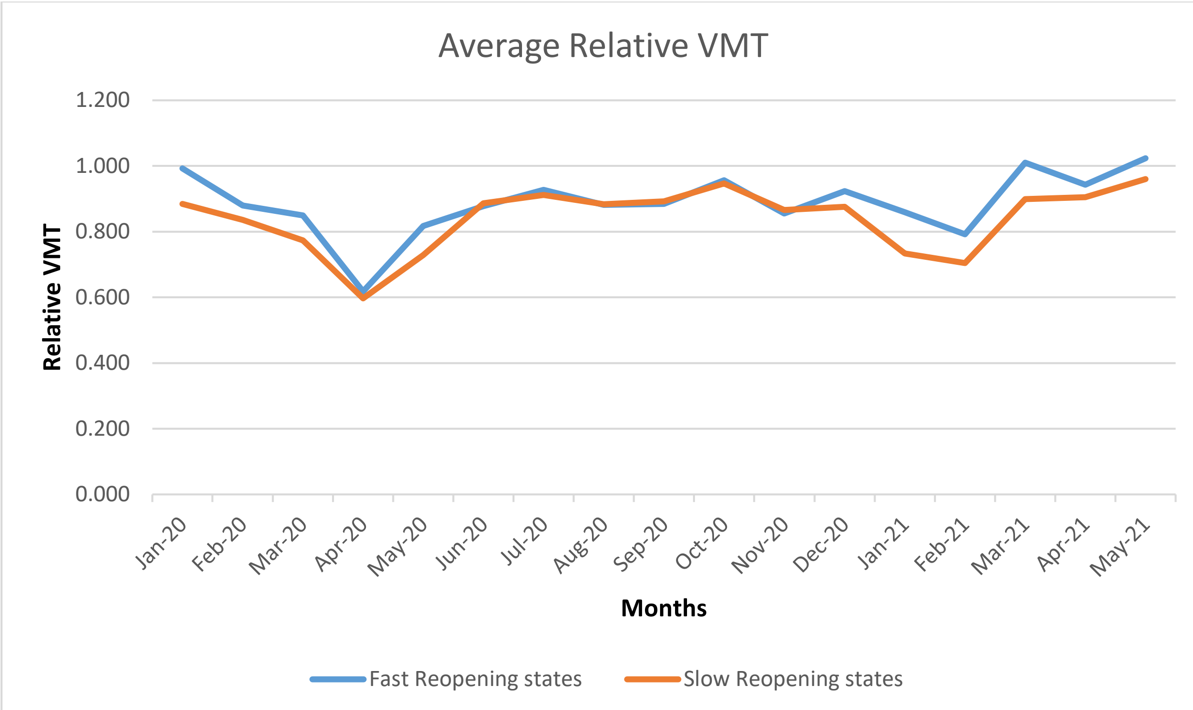


Figure 11. Average Relative VMT for all 8 States

Capital Metropolitan Transit Authority

Transit ridership data from the Capital Metropolitan Transit Authority (CapMetro) in Austin was analyzed to identify trends for the period between the years 2019 to 2021. This timeline was selected to consider pre–COVID-19 and during–COVID-19 periods. The information on the transit service, buses, frequency, and routes was gathered from the CapMetro website (https://www.capmetro.org/). CapMetro serves a population of more than 1 million with a service area of 535 square miles and a fleet of 82 buses. The facilities include 2,400 bus stops and 17 park-and-ride facilities. MetroRail, MetroRapid, Express, and Frequent are the major core service transit options of CapMetro (Capital Metropolitan Transportation Authority, 2022).

The pandemic resulted in operational changes due to reduced demand, increasing costs, and unsure budgets. To understand the effect of the pandemic on transit use, the ridership change for Austin METRO was analyzed. The analysis attempted to examine ridership changes for both captive and choice riders. With increasing telework, the aim of the analysis was to understand whether the ridership change was different for commuter-oriented and regular routes. The routes were categorized into Minority, Non-Minority, Downtown, and Suburban. The criteria and route number in each category are explained below.

Bus Route Classification

<u>Minority vs. Non-minority</u>
The information about the low-income/high-minority routes was gathered from the officials of CapMetro. Figure 12 shows the map of the service area, block groups, and routes. The routes were categorized as minority if the total miles of that route within a minority block group is more than 33% of

its total miles. The block groups with a minority/low-income population greater than 50% were considered minority block groups. Fifty-six out of the 81 routes were categorized as minority routes.

Downtown vs. Suburban

All the routes that served the central business district or downtown were populated under the category of downtown routes. The routes under the suburban category were the ones that bypassed the downtown. Thirty-two routes were categorized as suburban whereas 34 routes were grouped as downtown.

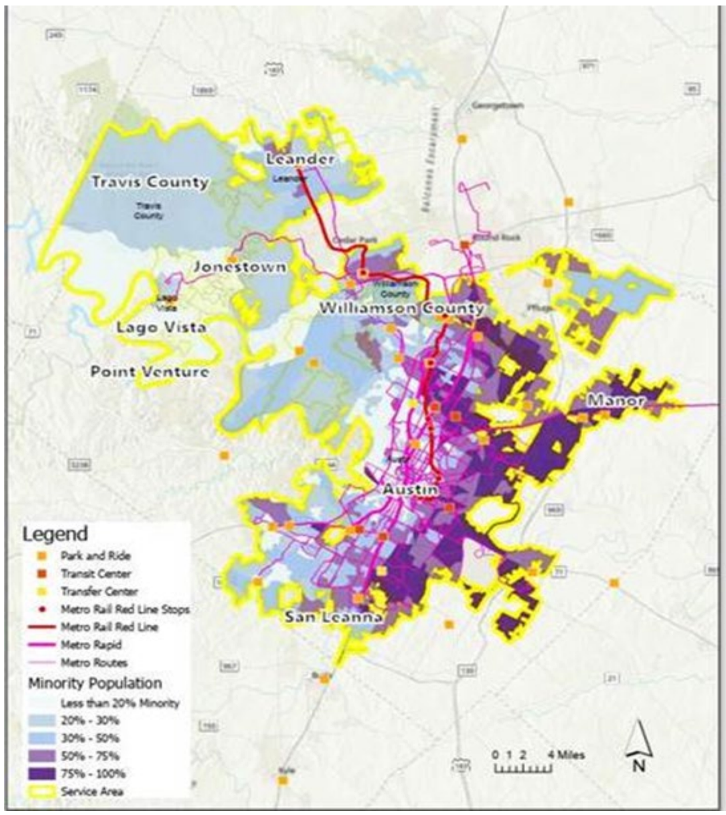


Figure 12. CapMetro Service Area Boundary, Routes, and Block Groups (Source: CapMetro)

Analysis and Results

Inaccurate or incomplete data was removed from the analysis. The specific routes and the criteria to remove them are:

- *Routes 152, 445, 451, 454, 455, 470* – These routes are special service routes that serve the population on demand. Therefore, these routes had a significant number of months with no ridership and thus we decided to avoid these routes in our analysis.
- *Routes 410, 411, 412* – These routes are the special service E-Bus routes that provide safe ride services late-night/early morning from the entertainment district. These had ridership data until the beginning of COVID-19 (March 2020). These routes had no ridership after March 2020. As

these routes had no alternative route running after March 2020, so they omitted them from the analysis. This was done to make sure that the analysis looked at the changes in ridership as effects only due to COVID and not due to any external reason.

The ridership for the routes that were shut down after March 2020 and were not operational were considered in the analysis only if they had an alternative route running after March 2020. It was assumed that riders could switch to the alternative route. If no alternative route was found, ridership was not considered in the analysis.

The weekday and weekend data for the average daily ridership of each route were examined. The pivot table function in MS Excel was used to filter the category of routes and day type. Beginning in March 2020, overall transit ridership plummeted for all categories of routes. Non-minority route's weekday ridership decline (71%) was larger than minority routes (61%) as shown in Figure 13. The data showed consistent results with past literature showing a smaller drop in ridership in neighborhoods with a high share of low-income and people of color residents. The trend in Figure 13 shows that as of December 2021 ridership is 51% below the pre-pandemic level for non-minority routes and 42% below for minority routes. It is worth noting that the decline in ridership during weekends was less compared to weekdays. After May 2021, the monthly decrease in weekend ridership for non-minority routes was either lower or equal to minority routes. This could be due to the high-income population using transit comparatively more for shopping trips compared to work trips. A similar pattern is observed in the literature where the data from a stated survey shows a shift in the primary purpose of traveling from work to shopping due to COVID-19 (Abdullah et al., 2020). Similarly, downtown routes saw a substantially greater daily ridership reduction (66%) than suburban routes (49%) as shown in Figure 14. The increase in the percentage of the teleworking (work from home) population explains the difference in ridership decline for both the categories. These results were similar to the travel patterns found in the central business district of Melbourne Australia, where there was a greater modal shift from transit to car driving in downtown areas (Currie et al., 2021).

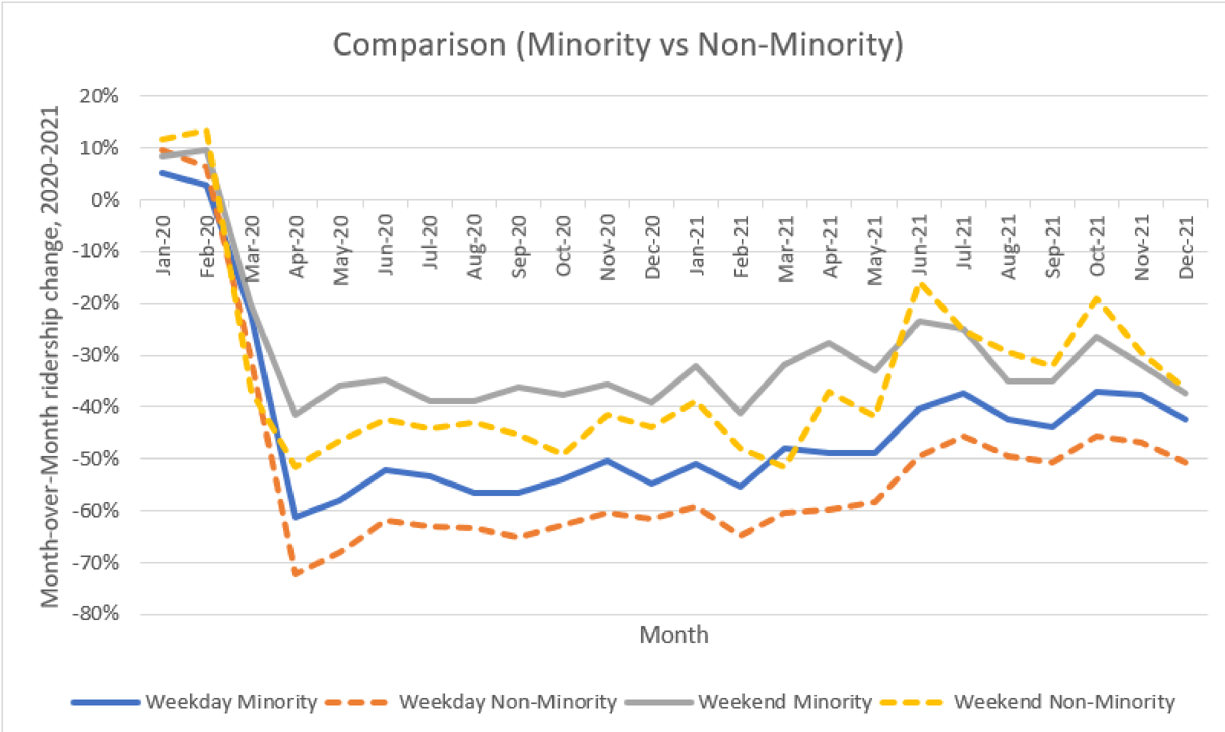


Figure 13. Average Daily Ridership Change (Minority vs. Non-minority Routes)

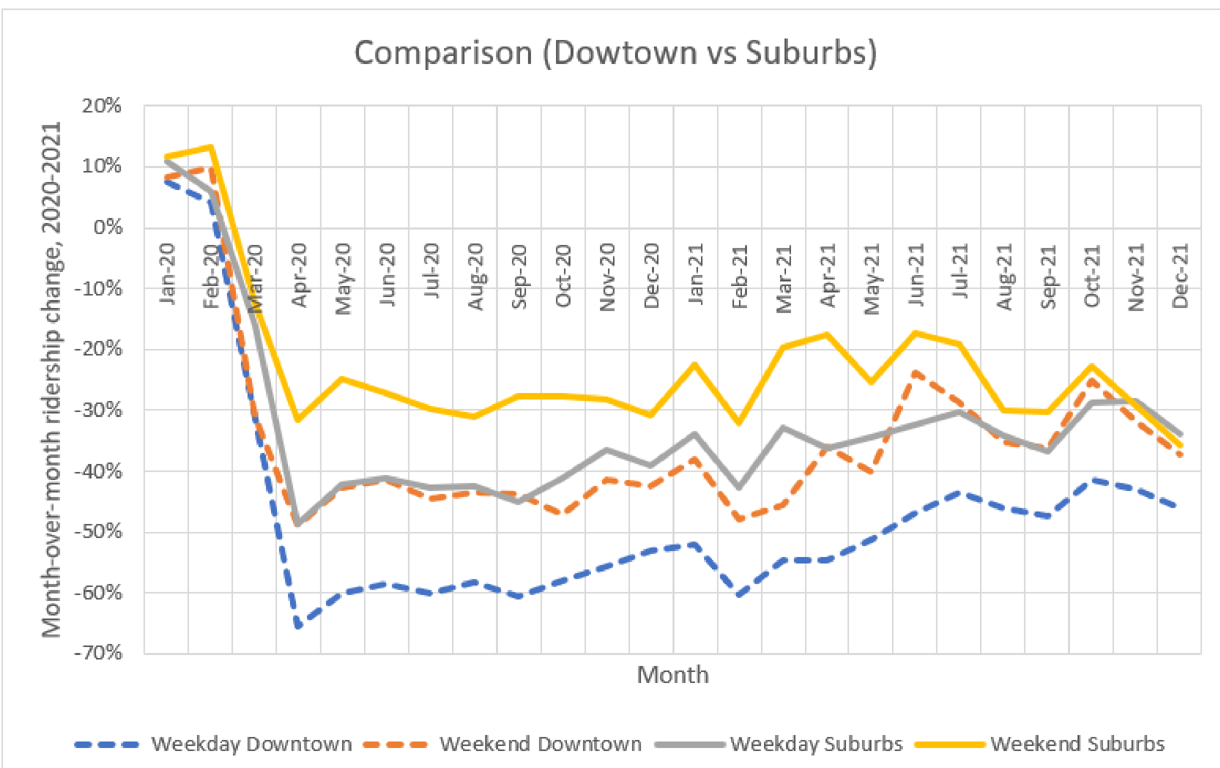


Figure 14. Average Daily Ridership Change (Downtown vs. Suburb Routes)

Tren Urbano and Bus Services in Puerto Rico

Ridership data from nine transit operations in Puerto Rico was analyzed to study the effect of COVID-19 and the local measures taken against the spread of COVID-19 on ridership. Annual Unlinked Passenger Trips (UPT) data for the 2018–2021 period was retrieved from Transit Agency Profile Reports of the National Transit Database (NTD). NTD data from the Tren Urbano (TU) heavy rail, AMA and Metrobus intermunicipal bus services, and six municipal bus operations was used to compare ridership levels before and after the COVID-19 emergency declaration in March 2020. Daily entries per TU station from January 2019 to July 2021 were also used to estimate ridership changes for the 16 months after the emergency declaration. The station entries for TU were supplied by the operator ACI-Herzog.

Description and Condition of Transit Operations

Figure 15 shows the network of transit operations owned by the Government of Puerto Rico in the San Juan Metropolitan Area (SJMA). The map shows the routes for the TU, AMA and Metrobus, and ATM passenger ferry across the San Juan Bay. Other transit services are offered in this SJMA region (not shown in Figure 15) by municipalities and “*porteadores públicos*” (jitneys). The “*Públicos*” are individual private operators on fixed routes using a shared demand response scheme with no service frequencies. About 200 “*Público*” routes were authorized in the SJMA, as of 2016 (PRHTA, 2018).

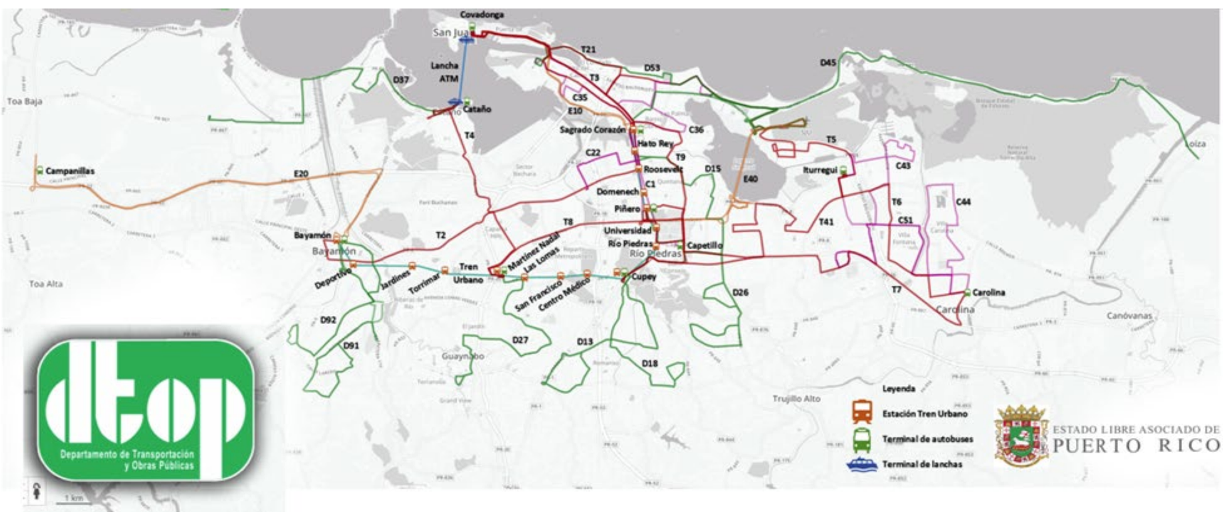


Figure 15. Network of Government-Owned Transit Operations in SJMA

TU is a 10.7-mile long heavy rail system with 16 stations on a single line connecting sectors of Bayamón, Guaynabo, and San Juan municipalities. The TU has a service area of 149 square miles and a population of 701,366 inhabitants (FTA, 2023). The first TU line started operations in 2005. The master plan of the heavy rail system included four additional lines, serving the SJU International Airport, the cruise ship ports to the South of historic Old San Juan, the municipalities of Carolina and Caguas, and other major destinations in the SJMA. The additional lines have yet to be constructed, so the length of the current line has restricted the effectiveness of the service and has not reached the projected estimate of 115,000 daily riders. The highest ridership for TU was 37,706 weekday trips in 2014 (Fischbach et al., 2020).

Metrobus operates in the TU service area, functioning as a major feeder service. The eight-route system includes four express bus routes to Old San Juan, the SJU International Airport, and the municipalities of Toa Baja (to the East of SJMA along a busway on freeways PR-22 and PR-5) and Caguas (to the South of SJMA along freeway PR-52). Metrobus had an annual UPT of 1.75 million trips in 2013, for approximately 7,800 weekday riders (FTA, 2023).

AMA is the largest (and oldest) bus operation in the SJMA with 23 fixed routes. The AMA service area covers sectors from eight municipalities in the SJMA with 198 square miles and 1.17 million inhabitants (FTA, 2023). AMA had an annual UPT of 10.25 million trips in 2013, or approximately 35,171 weekday riders (FTA, 2023). A major reorganization of AMA's operation was implemented in August 2015 in response to the economic crisis, population shifts, and a diminished bus fleet. The number of routes operated by AMA was reduced from 37 to 23. The reorganization included removing AMA routes that overlapped with existing municipal bus routes, transferring local routes to municipalities, enhancing service frequency by assigning more buses per route, and the realignment of routes to serve new and denser destinations.

NTD data from six local bus services, operated by the municipalities of Bayamón, Caguas, Carolina, Guaynabo, Mayagüez, and Ponce were also analyzed. These bus services operate exclusively inside municipality limits, connecting rural communities with their respective urban areas, with primarily daytime weekday schedules. Bayamón, Guaynabo, and Carolina are part of the core area of SJMA (along with San Juan and Cataño) with service area populations (SAP) of 65,706, 83,728, and 176,762 inhabitants, respectively. Caguas is also part of the SJMA but is located 16 miles south of San Juan, with an SAP of 131,438 inhabitants. Ponce is in the Southern Region of Puerto Rico, 76 miles away from San Juan, with an SAP of 79,650 inhabitants. Mayagüez is in the Western Region, 120 miles from San Juan, and has an SAP of 71,264 inhabitants. The Municipality of San Juan was not included in the analysis as 2021 NTD data show no records of its operation.

Pre–COVID-19 Circumstances in Puerto Rico

Puerto Rico has built an extensive highway network with 4,813 miles and 11,256 lane-miles (PRHTA, 2018). Automobile ownership in Puerto Rico is 146 vehicles per road mile, thus about 90% of the travel demand is satisfied using private motor vehicles. Peak modal share estimates in 2016 were 87.5% for auto, 8.3% for non-motorized modes, and 4.2% for transit in San Juan. Peak modal shares for areas outside San Juan were 94.9% for auto, 3.9% for non-motorized modes, and 1.2% for transit (PRHTA, 2018).

A sequence of major events occurred before COVID-19 in Puerto Rico that severely impacted the quality of life of the residents and subsequently reduced transit ridership. Puerto Rico has been immersed in a long and severe economic slump since 2006 that has resulted in a 12% reduction in population between 2010 and 2020 (New York Fed, 2023). The economic crisis for the U.S. territory toughened in September 2017 with the passage of Category-4 Hurricane María with 155-mph sustained winds through the territory. The TU rail stock and stations suffered major damage during the storm, causing the service to stop operations for three months. AMA and Metrobus also endured operation stoppages for two weeks after the storm (Fischbach et al., 2020). The impact from the economic situation and the hurricane resulted in a 27% reduction of the Puerto Rico labor force from April 2006 to October 2017. As population and labor force declined, a reduction in transit ridership was likely. The TU ridership decreased by approximately 30% and has still to recover to pre-María ridership levels as of May 2021 (FOMB, 2021). Ridership for AMA has severely suffered from a gradual and sustained reduction in ridership since 2009, from having more than 100,000 weekday trips in 2003 to just 4,277 in 2020 (Fischbach et al., 2020; FTA, 2023).

COVID-19 Spread Control Measures in Puerto Rico

A description of disease control measures implemented by the Government of Puerto Rico that had a direct impact in transportation is included to provide a local context of the situation of the pandemic since the Presidential Declaration of Emergency was made on March 13, 2020. The Government of Puerto Rico enacted Executive Order (EO) OE-2020-023 on March 15, 2020, implementing strict disease control measures for a two-week period. The order included the closure of non-essential public and private operations, social isolation, and home curfew orders for all citizens from 9 pm to 5 am. The order only allowed the operation of certain establishments providing carry-out or delivery food sales, banking institutions, gas stations, and health and medical services. Remarkably, transit services were not recognized as an essential service and TU, AMA, Metrobus, and ATM Metro ceased operations as a disease control measure. Municipal bus services, *públicos*, taxi and shared transportation services across the territory also followed the order immediately.

Executive Order OE-2020-029, effective on April 1, 2020, implemented stricter measures, increasing the curfew two additional hours, from 7 pm to 5 am, and establishing a restriction on the use of motor vehicles using a license plate scheme. Vehicles with a license plate ending on an even number were authorized to operate only on Mondays, Wednesdays, and Fridays, whereas vehicles with plates ending with an odd number were only authorized on Tuesdays, Thursdays, and Saturdays. The plate number restriction did not apply on Sundays, as the new order closed all non-essential businesses on this day, except for pharmacies, hospitals, and gas stations. Teleworking practices were encouraged in the order, allowing employers and employees to enter workplaces for four hours on a specific day to pick up the required equipment and materials.

As the pandemic emergency continued, and after one month of shutting down most businesses and services, OE-2020-033 was effective on April 13, allowing more categories of services and business to operate outside of the curfew hours (returning to the 9 pm to 5 am period). The license plate restrictions on motor vehicle usage were eliminated.

The following list includes a review of the relevant measures implemented on subsequent executive orders that directly or indirectly related to transportation and travel (LexJuris, 2021):

- OE-2020-038 (Phase 1), effective on May 4, 2020: Taxi services and “porteadores públicos” were allowed to operate as delivery services of merchandise and goods.
- OE-2020-041 (Phase 2), effective on May 26, 2020: Restricted capacities of 25–50% were established for restaurants, supermarkets, grocery stores, wholesale, and retail stores, with additional services allowed to operate (e.g., enclosed shopping malls, car dealers).
- OE-2020-044 (Phase 3), effective on June 16, 2020: The lockdown of non-essential services and businesses was lifted, although curfew was still in place from 10 pm to 5 am. Restricted capacity was at 50% with additional services allowed to operate (e.g., movie theaters, museums, beaches, fitness clubs); taxis and “públicos” and the AMA paratransit service were allowed to carry passengers.
- OE-2020-048 (Phase 4), effective on July 1, 2020: Restricted capacity increased to 75% for most services and businesses; transit services from TU, Metrobus, AMA, and ATM Metro were allowed to resume services with capacity restrictions, selected government employees were

authorized to return to their workplaces, with public allowed to visit government agencies five days later.
- OE-2020-054 (Phase 4), effective on July 23, 2020: As COVID-19 cases resurged from the opening of businesses, restricted capacity was reduced again to 50% for most businesses and transit services were shut down again, except AMA’s paratransit service.
- OE-2020-077, effective on October 16, 2020: Transit services of TU, Metrobus, AMA, and ATM Metro allowed to resume operations on October 26, 2022, under in-vehicle capacity restrictions.

A new Governor of Puerto Rico took oath on January 2, 2021. The new administration quickly established a different public policy for the control of the pandemic. The following list includes a review of the relevant measures implemented that were directly or indirectly related to transportation and travel:

- OE-2021-010, effective on January 8, 2021: Curfew was reduced from 11 pm to 5 am and Sunday's lockdown order was eliminated. Gyms, casinos, and cinemas were again allowed to open with 30% capacity.
- OE-2021-014, effective on February 8, 2021: Curfew was again reduced from 12 to 5 am; allows the limited use of beaches, swimming pools, natural reserves, golf courses, parks, courts, gyms, and galleys without the consumption of alcoholic beverages. All public schools must be ready to resume in-person activities in March 2021.
- OE-2021-017 orders that public and private schools resume in-person activities on March 1, 2021, with a 50% capacity restriction.
- OE-2021-036, effective on May 24, 2021: Eliminates the curfew restrictions initially implemented in March 2020. Capacity restrictions for specific business and services were still under restricted capacities between 30 and 50%.

The previous list was not intended to be comprehensive of all the local control measures implemented in Puerto Rico. Other measures were implemented such as vaccination requirements and mask mandates, among many other strategies. As new variants of the disease continued to alter the contagions and related deaths, the lockdown of operations, curfew hours, restricted capacity levels, alcohol sales, in-person activities, and other mandates were frequently modified (increased or reduced). As of February 6, 2023, a total of 1,120,835 cases and 5,712 deaths have been recorded in Puerto Rico (New York Times, 2023). January 2022 was recorded as the month with the highest average cases and deaths in Puerto Rico.

Ridership Analysis for the Before and After COVID-19 Emergency

Table 1 presents the annual UPT reported during the 2018–2021 fiscal years for nine transit services in Puerto Rico. The average UPT was calculated for the 2018–2019 period to establish a pre–COVID-19 benchmark for the comparison with the year 2021. The average 18-19 UPT blends the combined impacts from the major circumstances leading to the reduction in population and transit riders prior to the COVID-19 pandemic declaration in March 2020. The UPT 2020 includes data from eight months prior to the emergency declaration so it was not included in the analysis. The percent change was then calculated between the total 2021 UPT and the average 2018–2019 UPT values.

Table 1.Change in UPT of Selected Transit Services in Puerto Rico

Transit System	UPT 2018	UPT 2019	Average 18-19 UPT	UPT 2020	UPT 2021	% Change 18-19 vs 21
Tren Urbano	3,800,430	5,345,703	4,573,067	3,531,150	836,028	-81.7
Metrobus	1,198,068	1,482,803	1,340,436	1,032,480	409,111	-69.5
AMA	3,210,200	3,224,376	3,217,288	2,001,263	839,200	-73.9
Bayamón	246,436	293,219	269,828	185,046	68,719	-74.5
Carolina	501,364	535,717	518,541	287,458	127,990	-75.3
Guaynabo	307,753	492,791	400,272	305,989	122,634	-69.4
Caguas	172,210	164,842	168,526	109,894	29,105	-82.7
Mayagüez	151,602	187,741	169,672	116,743	46,683	-72.5
Ponce	451,248	453,886	452,567	313,667	97,647	-78.4

Note: NTD reports are based on fiscal year; thus UPT 2018 includes data reported from July 2017 to June 2018.

Even though AMA has the largest service population of transit services in Puerto Rico, the TU had the top annual UPT value for the before COVID-19 period with 1.36 million trips more than AMA. Consider that the TU SAP is 50.6% smaller than AMA's. Another remark for the before COVID-19 period is that eight transit services, excluding Caguas, reported increases in UPT for the year 2019 when compared with 2018. TU and Metrobus recorded the two largest increases in total UPT in 2019. In terms of percent change between 2019 and 2018, Guaynabo (60.1%), TU (40.7%), Metrobus (23.8%), and Mayagüez (23.8%) had the largest increases in trips in 2019. On the other hand, Caguas recorded a 4.3% reduction in trips in 2019.

UPT data for the report year 2020 and report year 2021 was affected by the shutdown order of transit services from March 15 to July 1, 2020, and from July 23 to October 16, 2020, respectively. Transit operations in Puerto Rico were completely shut down for 195 days in 2020. Combined with stay-at-home orders, teleworking, and the closure of non-essential business, services and workplaces, the immediate impact on transit ridership is clear. There were 8.5 million annual trips less for the nine transit services in report year 2021, compared to the 2018–19 average. TU and AMA recorded the largest reductions in annual UPT with 3.7 million and 2.4 million trips, respectively. These results should not be shocking as these two services also had the top two ridership levels before the pandemic in Puerto Rico.

The percentage change in UPTs between the before and during COVID-19 periods was also analyzed. Guaynabo had the minimum reduction in UPT of 69.4%, Metrobus the second lowest reduction with 66.9%, and AMA the third lowest with 70.2%. On the other hand, Caguas registered the maximum reduction of 82.7% and TU the second highest with 81.7%. The results tend to identify TU as the transit service mostly affected by the local measures used to control the spread of COVID-19 in Puerto Rico. Boarding data per station was also analyzed to identify temporal effects in TU ridership.

The NTD publishes vehicle revenue hours (VRH) and UPT/VRH (or passengers per hour, PPH) values as a service effectiveness performance measure. PPH reflects how many passengers per vehicle rode during a single hour of revenue for the before and during COVID-19 periods. Figure 16 shows PPH values for the nine transit services for the 2018–2020 period. The average value for the 2018–2019 period was calculated and compared against the 2021 value to estimate the impact from COVID-19 countermeasures.

The TU, with 52 PPH, unquestionably had the top service effectiveness for the before COVID-19 period. The high service performance for TU was expected due to its higher vehicle capacity to carry more passengers than fixed-route bus operations do. Ponce (27 PPH), Carolina (22 PPH), and Guaynabo (22 PPH) had the top three PPH for the before COVID-19 period of the bus services. In contrast, Mayagüez and AMA reported the two lowest service effectiveness for the before COVID-19 period. The Mayagüez service is a relatively young operation (10 years), with six of its ten routes starting operations in 2016. AMA, on the other hand, is an established operation that is enduring a severe sustained drop in ridership because of historically unreliable operations, fiscal challenges, and other externalities.

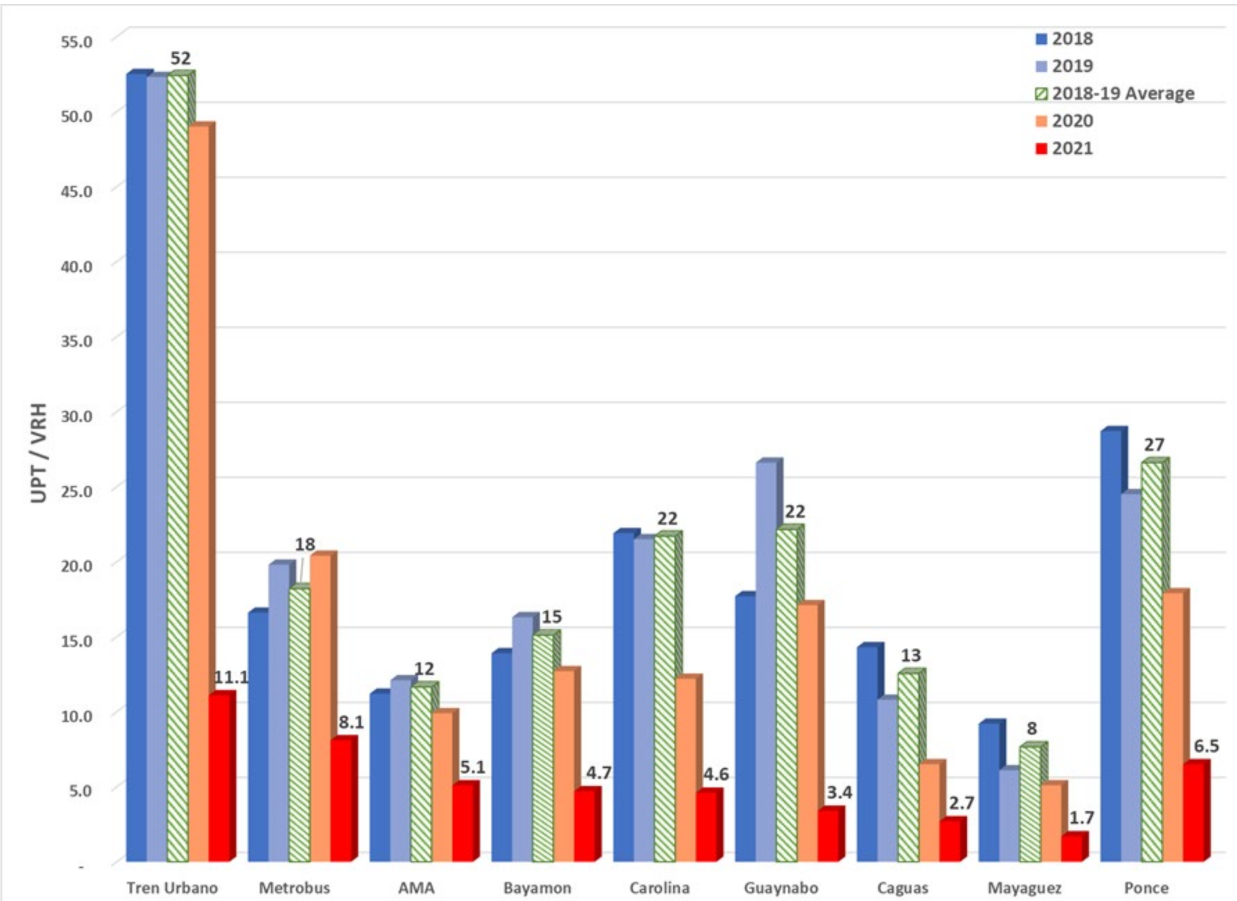


Figure 16. Passengers per Hour of Puerto Rico Transit Operations

The TU, Ponce, and Guaynabo services experienced the largest drops in service effectiveness during the COVID-19 period with PPH reductions of 41.3, 20.1, and 18.8, respectively. A PPH of 49 for TU in report year 2020 is slightly lower than the national average PPH of 54.9 for heavy rail operations in the U.S. (FTA, 2020). A much larger impact from COVID-21 control measures is reflected on TU ridership in report year 2021. Bus operations in Puerto Rico do not exhibit a better performance. The national average PPH for motorbus services was 20.7 in 2020 (FTA, 2020). Only Metrobus had a comparable performance to the national average with a PPH of 20.4 in 2020. Interestingly, Metrobus had a slightly higher PPH in 2020 than in report years 2019 and 2018. The other bus services exhibited decreases in PPH in 2020, with Mayagüez, Caguas, and AMA having the lowest service effectiveness.

In terms of percent change, Guaynabo, Carolina, and TU had the largest reductions in PPH in 2021 when compared with the before COVID-19 period. These operations had the three largest percent reductions in PPH of 84.7%, 78.8%, and 78.8%, respectively. In contrast, Metrobus and AMA reported the smallest percent reduction in PPH with 55.5% and 56.2%, respectively.

Daily Station Entries in Tren Urbano

Daily entries per TU station from January 2019 to July 2021 were analyzed to identify the shifts in ridership that occurred between the before and during COVID-19 periods. Table 2 shows the total entries and the average daily entries per month for the heavy rail service. As stated in Chapter 4, local executive orders called for the shutdown of transit services in Puerto Rico on two occasions as a disease control measure. Therefore, TU did not have revenue service from May 16 to July 11 and from July 23 to October 25, 2020. Table 2 also shows the percent change for the average daily station entries. The percent change was calculated comparing each month since January 2020 against its corresponding month in 2019.

The before COVID-19 period shows a decreasing ridership trend with the lower values during June, July, and December on calendar year 2019. These months correspond to the summer and holiday periods, during which the University of Puerto Rico at Rio Piedras (UPR-RP) and the Sagrado Corazón University (SCU) have semester breaks. UPR-RP has two station gates at Universidad Station. UPR-RP student residence areas are also located in the vicinity of the Rio Piedras Station. SCU is located in the neighborhood of the Sagrado Corazon Station, the last station of the alignment in the Santurce neighborhood. March and October 2019 represent the two months, in each semester, with the highest total entries in TU in that year.

The total entries for the first three months of calendar year 2020 shows a sustained reduction in riders, except for a small increase in February. In terms of daily entries, the first three months of 2020 had an average reduction of 17% compared against the corresponding months of 2019. This decrease in ridership can be associated with the external factors to COVID-19 that were explained in Chapter 4.

Table 2. Monthly and Average Daily Entries for Tren Urbano

Before COVID-19 Declaration				After COVID-19 Declaration			
Month	Station Entries	Average Daily Entries	% Change 2019	Month	Station Entries	Average Daily Entries	% Change 2019
Jan-19	470,889	15,190	-	Apr-20	0	0	-100.0
Feb-19	444,675	15,881	-	May-20	0	0	-100.0
Mar-19	497,812	16,058	-	Jun-20	0	0	-100.0
Apr-19	449,828	14,994	-	Jul-20	31,619	2,874	-75.3
May-19	433,192	13,974	-	Aug-20	0	0	-100.0
Jun-19	356,593	11,886	-	Sep-20	0	0	-100.0
Jul-19	360,919	11,643	-	Oct-20	14,314	2,386	-85.7
Aug-19	433,478	13,983	-	Nov-20	66,167	2,206	-84.4
Sep-19	442,937	14,765	-	Dec-20	76,943	2,482	-81.1
Oct-19	516,308	16,655	-	Jan-21	79,784	2,574	-83.1
Nov-19	422,957	14,099	-	Feb-21	95,116	3,397	-78.6
Dec-19	406,374	13,109	-	Mar-21	115,758	3,734	-76.7
Jan-20	321,809	11,097	-26.9	Apr-21	110,986	3,700	-75.3
Feb-20	425,749	14,681	-7.6	May-21	118,962	3,837	-72.5
Mar-20	200,943	13,396	-16.6	Jun-21	126,423	4,214	-64.5
				Jul-21	131,053	4,228	-63.7
Average	**412,298**	**14,094**	**-17.0**		**60,445**	**2,227**	**-83.8**

The substantial impact to the TU ridership after the emergency declaration of March 2020 resulted in a reduction of 4.098 million daily entries in 2020, when compared to calendar year 2019. Considering the difference in operating days by months due to the shutdowns, the reduction in daily averages between the before and during periods was compared, showing an indisputably severe reduction of 11,867 less daily entries, for an 83.8% reduction. The TU resumed revenue operations in October 2020, after the repeal of the second (and last) shutdown order, registering an 85.7% reduction in average daily entries in comparison with October 2019. As the curfew and stay-at-home instructions were adjusted after October 2020 to allow more services and workplaces to return to in-person operations (although still with restrictions in capacity), TU average daily entries gradually increased from 2,386 to 4,228, as shown in Table 2. By July 2021, the 16th month after the COVID-19 emergency declaration, the percent reduction in average daily trips was still 63.7%, when compared with July 2019.

A comparison of the share in average daily entries for each TU station for the before and during COVID-19 period was made to identify increases and decreases in the share of entries per each station. Figure 15 shows the TU alignment with its 16 stations, starting from the Bayamon Station in the west end to the Sagrado Corazon Station in the east end of the rail line. Figure 17 shows the share of average daily entries per TU station for the before and during periods, along with the percentage change between the two periods. The values per station in the figure are shown from top to bottom in the order of the TU stations in the westbound direction (from Sagrado Corazon to Bayamon).

The stations with the largest share of entries in the rail line for the before COVID-19 period were Sagrado Corazon (13.9%), Bayamon (12.5%), Deportivo (10.2%), and Río Piedras (8%). Sagrado Corazon Station, at the east end of the TU alignment, is a major transit transfer hub with other transit services. This station is in the highly populated Santurce neighborhood with residential, commercial, educational, and institutional activities. Bayamon and Rio Piedras stations are adjacent to the two urban cores of Bayamon and Rio Piedras. Deportivo is adjacent to a sports complex, a regional court of justice, and a major shopping center. On the other hand, the stations with the lowest share of daily entries in the before period were Jardines (1.8%), Torrimar (2.1%), and Las Lomas (2.8%). These three stations are in predominantly low to mid density residential areas.

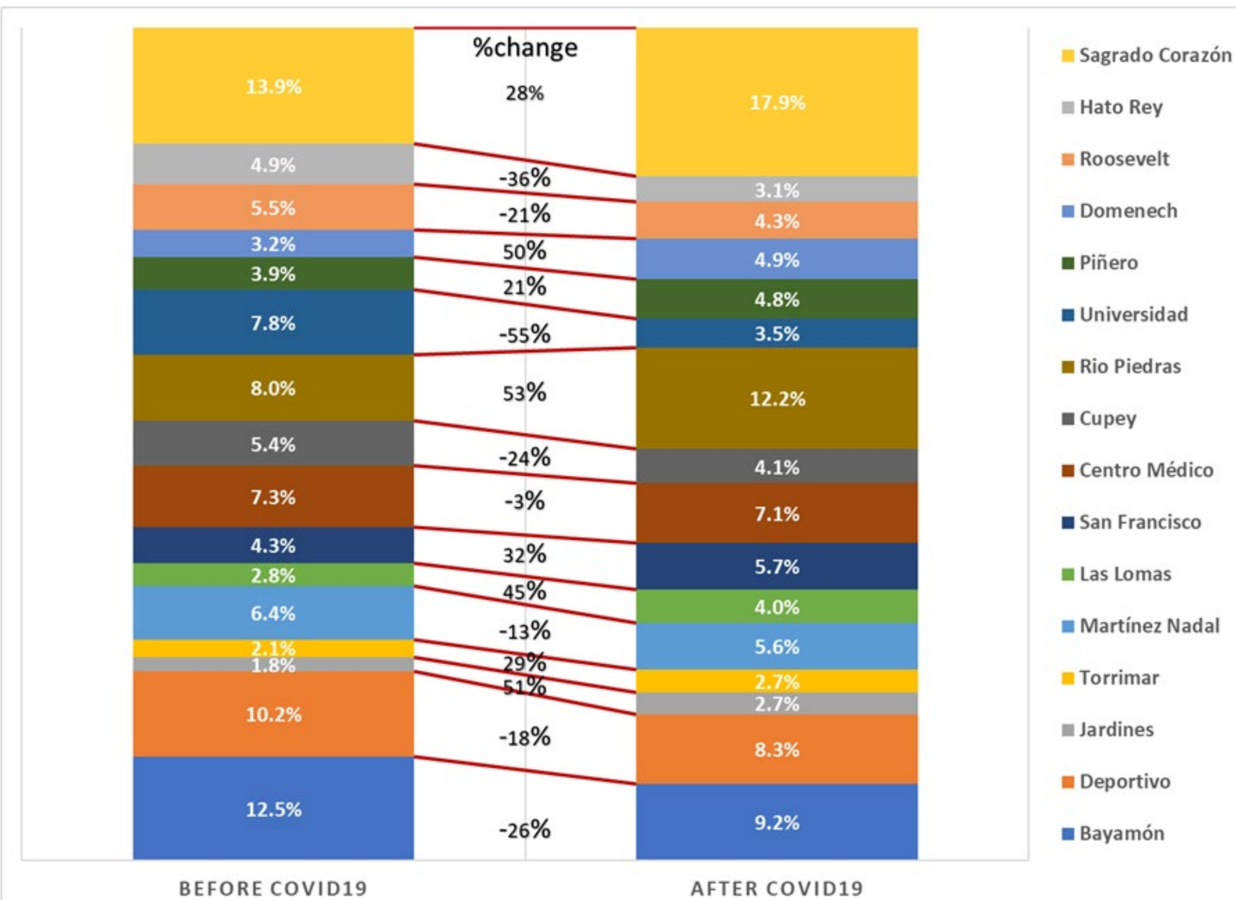


Figure 17. Share of Daily Entries per TU Station for Before and During COVID-19 Periods

The top four TU stations that increased their share of daily entries during the COVID-19 period were Rio Piedras (53%), Jardines (51%), Domenech (50%), and Las Lomas (45%) stations. These four stations are adjacent to residential communities, which might be indicative of citizens using the TU for mobility purposes during the pandemic for food and grocery shopping and for medical reasons, among other essential activities. Domenech Station is adjacent to multiple apartment towers exclusive for senior citizens and two hospitals. The Río Piedras Station is also enveloped by small retail and institutional services close to the UPR Rio Piedras Campus.

On the other hand, the top four stations that recorded a decreased share of daily entries were Universidad (-55%), Hato Rey (-36%), Bayamón (-26%), and Cupey (-24%) stations. Universidad and Cupey stations primarily serve the UPR Rio Piedras and Ana G. Mendez University, respectively. The two gates of Universidad Station are inside the UPR Río Piedras Campus. Classes were shifted to distance learning modes since the emergency declaration in March 2020. Therefore, universities restricted in-person activities inside their campus facilities, thus reducing the need to use TU. Bayamon and Hato Rey stations are located at two urban core sectors with several commercial and workplaces. Hato Rey Station is in the sector known as "The Gold Mile," surrounded by multiple banking and financial institutions, as well as the José Miguel Agrelot Coliseum, the largest indoor entertainment venue in Puerto Rico. Most of the workplace activities were shifted to telework and the coliseum venue was not being used as entertainment events and large group gatherings were not authorized. Bayamón Station, at the west end of the TU alignment, provides transfer to the Metro Urbano commuter bus route, which has about 2,000 daily riders. Although transfers between the two services are not known, the experience is that a large share of Metro Urbano users transfer to TU. Most of these commuters probably were working from home during the initial months of the pandemic. Also, Bayamon Station is next to a small university and two indoor shopping centers that during the first months of the pandemic were not active due to executive orders restricting indoor activities.

Background: Expert Interviews

To get a better understanding of how COVID-19 has impacted travel and may impact travel in the future, the research team talked to a panel of transit, toll, and travel experts. The transit expert panel consisted of representatives from Texas A&M (TAMU) transit service, Capital Metro transit agency, Puerto Rico Tren Urbano, and the Federal Transit Administration. The expert panel interviews were conducted in August 2021.

The first questions that were asked to the transit expert panel were about the COVID-19 impact on ridership and if their transit agency's ridership level has returned to the pre–COVID-19 level. The TAMU bus service indicated that a large demographic of riders consisting of students and faculty stopped using transit as the classes were moved online. Normally the service ran around 63 buses at peak hours from 6:30 am to 8:00 pm. However, it was pulled back to 58 buses and further reduced to 45 buses, as there was no clear picture of the number of riders and knowing that physical distance in the bus had to be maintained. Ridership decreased by 84% in the spring of 2020 but was anticipated to run full service in 2021 with mask and sanitizing mandates. The bus service is also dependent on student drivers who were not willing to operate the vehicles due to the risk of contracting the virus.

At the national level, transit ridership was 20% of normal levels in April of 2020 and eventually raised to 36% in July 2020 and hit 51% in June 2021. Primary and secondary trips made by the office workers who travel to the office and between office locations for meetings or any other events were lost during COVID-19 as the work-from-home situation emerged. This showed that the trip purpose has been the biggest obstacle in changing the transit ridership levels. The Capital Metro transit agency in Austin indicated that the transit ridership dropped to 30% of normal and saw a decline of more than 100,000 riders per week. Many riders lost were high school students and the student population from UT Austin and the University of North Texas. Many of the local riders who used transit during the pandemic were either grocery workers or in the medical field. In August 2021, transit returned to 60% of the normal ridership levels with more riders using the transit on weekends. With work from home trending in almost every business, commuter rail still struggles to get back to normal as it historically serves home to work and back trips.

In Puerto Rico, the government imposed strict curfew restrictions for a long period of time, and hence the Tren Urbano service was not provided for about 213 days. The heavy rail service restarted operations in October 2020, registering 36% of its normal ridership level in 2021. However, the transit agency is expecting an increase in ridership as universities restart in-person classes, as students represent 33% of their total ridership.

Another topic of discussion was about the strategies implemented by the transit service agencies to bring customers back. The common strategies included the installation of air cleaners, disinfection of the touchable areas on the buses, and imposing mask and sanitization regulations. The TAMU bus service used social media campaigns to explain how the buses were sanitized along with the safety measures followed to protect the community to increase ridership. Capital Metro partnered with H-E-B to deliver food to people on their doorsteps to improve the safety of people at home. Government officials In Puerto Rico used media outlets to gain confidence in transit among the public.

All the transit agencies in the panel expected ridership to return to normal either because of the work modes returning to in-person, people not being able to afford the cost of parking or having few parking areas. Some of the panel members stated that the fear of COVID-19 risk had a small effect on the reduction in transit ridership, and that people were making use of the higher flexibility to choose other travel modes. For work trips, some people might refuse to travel and vice versa happens when traveling for recreational purposes. Some panel members said that the fear factor was stated more as an excuse to keep working from home.

The panel member from Capital Metro transit agency in Austin stated that people's income and the type of job (being online) play a role in increasing transit ridership. The current scenario may have some analogy with slugging (this is a rare practice that occurs in three U.S. cities where riders and drivers meet and form impromptu carpools without knowing one another in advance). With cheap parking and reduced congestion, people tend to avoid slugging. Increased parking prices and congestion outweigh the fear of slugging and therefore people tend to slug. Cheap parking and reduced congestion are likely two of the reasons for the decline in transit ridership.

The panel of travel experts also talked about their experiences over the previous 18 months and what they anticipate will happen with transportation going forward. The statistical overview of travel during the pandemic and ideas for actions to be taken to enhance travel demand were reviewed. The Bureau of Transportation Statistics report on transportation demand was briefly summarized. Air travel in 2021 was still 20% below pre–COVID-19 levels. A better comprehension of the purpose of airline travel during COVID-19 is obtained with the use of airport-specific data, such as types of destinations. The demand for travel on the roads appeared to return to normal quickly after the first months after the declaration of the emergency. The freight data revealed a significant decrease during the Texas storms in February 2021.

COVID-19 has brought a change in the temporal and geographical distribution of travel. The number of trips in rural and urban counties has varied causing a shift of people moving from high-transit dependent areas to low-transit dependent areas. More riders have left large networks than smaller ones, and high-income riders were more likely to leave transit than low-income riders. The likelihood of Black riders leaving transit during the pandemic was the lowest. A rise in automobile ownership and a decline in transit use over the next one to two years can be anticipated as auto production rises. The panelists also mentioned that improvements made in the hybrid working environment may impact travel demand in the future.

Toll facility experts were interviewed to understand how COVID-19 affected toll facilities and their revenue. April 2020 saw a large decrease in traffic levels. However, the number of COVID-19 cases had no relationship with traffic levels as traffic was more dependent on policies and government curfews. The surge in COVID-19 cases in 2021 was not related to a drop in traffic volumes. Traffic data from May 2021 shows that traffic has rebounded fully to pre-pandemic level for most toll roads. However, traffic and revenues on express lanes have not yet recovered to pre-pandemic levels. The daily traffic analysis reveals that the morning peak is still down whereas the evening peak has recovered. There is a shift in travel from morning peak to midday and evening periods. The travel lanes are flowing better thus increasing speed and travel time savings compared to pre–COVID-19. A lower percentage of transponders during the peak and higher usage in the off-peak indicate newer drivers hitting the roads. Flexible working hours could also be the reason for the higher off-peak transponder penetration. These travelers are going to the workplace later in the day or working from home making shopping trips in the afternoon. This effect shows that trip purpose had a major impact on transponder transactions. Weekend traffic in express lanes is higher than during pre–COVID-19 periods. Long-term highway project plans were not altered due to COVID-19 as the travel demand is expected to rebound in 3 to 4 years. Fitch ratings did not downgrade the bond ratings for the toll agencies. Thus, investors and rating agencies have faith in the continued recovery and financial strength of the toll facilities.

Chapter 5. Travel Survey

Based on the travel data examined, the information obtained from the literature reviewed, and the discussion with experts it was clear that transit was experiencing the greatest impact from COVID-19 of all transportation modes. Therefore, the activities for the ensuing phases of the study were focused on transit. This chapter presents the survey development, administration, and findings.

Travel Survey Development

The impact by mode of the pandemic found in the literature and the expert interviews lead us to focus the survey on transit ridership. The goal was to better understand travelers' willingness to return to transit versus their fear of COVID-19 to better predict future transit ridership. Some of the research questions that arise are: Does psychology/stress play an important role in travel behavior, especially transit use? How is fear of COVID-19 related to present and future transit use? What are the factors contributing to the reduction of transit ridership? To address these questions an online 40-item questionnaire was developed. The questionnaire was available in English or Spanish. Appendix A presents the survey questionnaire. The survey questions were divided into five categories:

1. Socioeconomic status and demographic characteristics.
2. Current, past, and potential travel using transit.
3. A standardized block of ten questions known as the Perceived Stress Scale (PSS), developed by Cohen et al. (1983), that quantifies the level of stress in a person.
4. A standardized block of seven questions known as Fear of COVID-19 (FCV), developed by Ahorsu et al. (2020), that quantifies the level of fear of getting the disease in a person.
5. First-person videos of a crowded stop bus and inside a crowded bus to detect the level of comfort of the respondents with that situation.

The FCV-19S instrument was included as part of the survey conducted in this study to assess people's fear of COVID-19. Appendix A shows the survey questionnaire used in the present study with the FCV-19S instrument included as questions 5.1 to 5.7.

Travel Survey Implementation and Data Collection

The survey was implemented online in Qualtrics during the months of May and June 2022. Incentives were provided to respondents by randomly drawing ten $100 gift cards. To get as large a sample as possible, and to minimize sampling bias, the survey was advertised widely, including Reddit (transit-related subreddits like Urban Planning, Transit, and Bus), LinkedIn (Texas Transportation Institute), service social media pages (e.g., Twitter, Facebook, and Instagram) from Texas A&M Transportation and the University of Puerto Rico at Mayagüez, and Bulk mail listservs (Texas A&M University students and employees, Transportation Demand Management listserve at the University of South Florida, and University of Puerto Rico at Mayagüez students and employees).

The survey received 7,443 responses. Responses that completed the survey in less than three minutes (933 responses) or not completed (210 responses) were removed, resulting in a sample of 6,300 responses. The three-minute criterion was chosen as a cut-off point as it was deemed unreasonable to read and answer the survey questions in a shorter time. As an internet survey, responses came from different countries, but the majority (94.7%) were from the U.S. based on IP address. The survey response map is shown in Figure 18. The bigger dots represent a larger number of responses from that location.

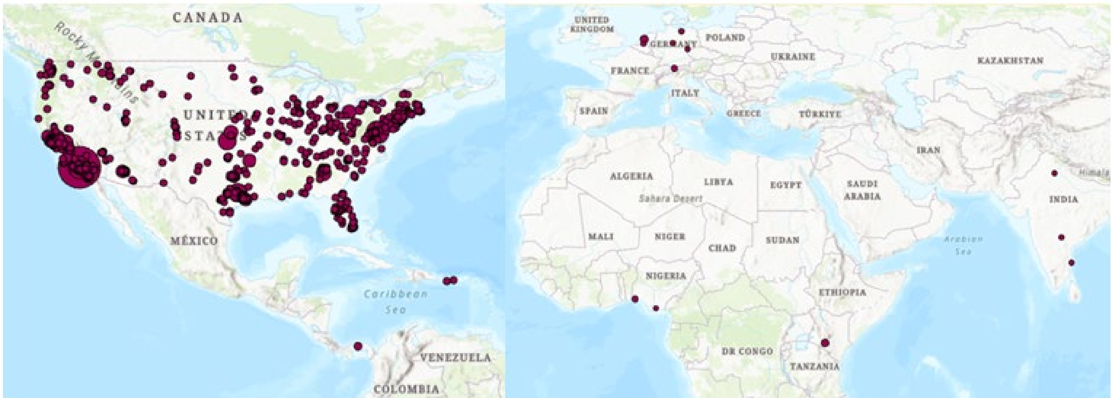


Figure 18. Travel Survey Response Map

The examination of the data found that responses from younger travelers, males, and several ethnicities were overrepresented in the sample, when compared with the U.S. population. Table 3 shows there are significant differences when comparing the original collected data with 2019 U.S. Census Data. To account for this, responses were weighted based on age, gender, and ethnicity to match the percentages from the 2019 U.S. Census Data (U.S. Census Bureau, 2021). RStudio was used to weight the categories, which aims to balance class distribution using built-in packages. The results discussed in this section use the weighted data. The demographic and transit usage data shown in Table 3 includes both international and U.S. responses. The survey allowed participants to identify their gender as '*Other' or "No Answer"*, whereas the U.S. census only includes male and female options. To match the census data, the '*Other'* and *'No Answer'* responses were given a weight of one. Table 3 shows the basic characteristics of the survey sample after data cleaning and weighting. It is interesting to note that 70.5% of the respondents stated not having contracted COVID-19. The U.S. CDC reported that almost 60% of the U.S. population has had COVID-19 by February 2022 (https://time.com/6170735/how-many-people-have-had-covid-19/). It might be plausible that participants did not want to share their health information, might have not been tested for COVID-19, or were infected but with no symptoms.

Table 3. Sociodemographic Characteristics and Stated Use of Transit

Characteristic		Percent in Each Category		
		Original Survey Data	**Weighted Survey Data**	**U.S. Census**
Age (years old)	18 ~ 24	11.0	12.4	12.4
	25 ~ 34	45.5	18.7	18.7
	35 ~ 44	16.9	16.9	16.9
	45 ~ 54	25.5	16.2	16.2
	Above 55	1.1	35.8	35.8
Ethnicity	White or Caucasian	49.1	66.6	66.6
	Hispanic	12.3	14.1	14.1
	Black or African American	10.9	11.1	11.1
	Asian	9.3	5.3	5.3
	Native American or Alaskan Native	11.7	1.0	1.0
	Multiracial or Biracial	6.5	1.7	1.7
	Others	0.2	0.2	0.2
Gender	Female	39.8	50.9	51.1
	Male	58.6	48.8	48.9
	Others / No Answer	1.6	0.36	-
Annual household income ($U.S. dollars)	Under 15,000	5.2	4.5	9.3
	15,000 ~ 24,999	15.0	8.9	8.1
	25,000 ~ 34,999	19.2	12.3	7.8
	35,000 ~ 49,999	16.9	18.7	10.9
	50,000 ~ 74,999	15.6	14.0	16.2
	75,000 ~ 99,999	12.9	15.8	11.9
	100,000 ~ 149,999	9.3	12.6	15.9
	More than 150,000	4.4	11.1	19.9
	Prefer not to answer	1.5	2.1	-

Characteristic		Percent in Each Category		
		Original Survey Data	**Weighted Survey Data**	**U.S. Census**
Current employment status	Full-Time	52.0	56.5	-
	Part-Time	19.4	11.7	-
	Student	11.2	10.2	-
	Homemaker	6.2	5.2	-
	Retired	5.6	11.6	-
	Unemployed	5.6	4.8	-
Contracted COVID-19	Yes	11.7	17.2	-
	No	78.6	70.5	-
	Unsure	8.9	10.2	-
	Prefer not to say	0.8	2.1	-
Do you own/have access to a motor vehicle?	No	8.0	8.1	-
	Yes	92.0	91.9	-
How often did you ride the bus/train (before COVID-19)?	More than 10 trips a week	7.4	9.1	-
	6 to 10 trips a week	27.5	22.5	-
	1 to 5 trips a week	31.1	25.6	-
	1 to 4 trips a month	23.3	23.1	-
	Less than 1 trips a month	7.2	9.8	-
	Never	3.5	9.9	-
Currently, how often do you ride the bus/train?	More than 10 trips a week	6.1	5.5	-
	6 to 10 trips a week	23.8	18.6	-
	1 to 5 trips a week	30.3	22.6	-
	1 to 4 trips a month	25.0	25.2	-
	Less than 1 trips a month	11.0	15.2	-
	Never	3.9	13.0	-

Characteristic		Percent in Each Category		
		Original Survey Data	Weighted Survey Data	U.S. Census
After COVID-19, will you ride transit more, less or the same amount as before COVID-19?	Less	50.6	45.5	-
	More	15.7	15.9	-
	Same	33.7	38.6	-
Do you now ride transit more, less or the same amount as before COVID-19?	Less	34.2	40.8	-
	More	21.2	18.8	-
	Same	44.5	40.4	-

Travel Survey Analysis

The sample was examined to identify frequent transit users. The hypothesis is that these respondents will present more relevant information when analyzing how their stress and fear of COVID-19 influences transit travel. Frequent transit users were defined in this study as respondents that stated using transit at least 1 to 5 trips a week. The weighted sample includes 57.2% frequent transit riders before the COVID-19 pandemic compared to just 46.7% during the pandemic. A large group of respondents stated they use less, or the same amount of transit as compared to before COVID-19 (40.8% used transit less and 40.4% the same). The willingness to use transit after COVID-19 was not as high as it was pre-pandemic since 45.5% of participants stated that they will use less transit in the future. The survey results appear to corroborate the literature on overall travel and transit use.

There are 4,183 respondents (unweighted number) that stated using transit at least once per week pre–COVID-19 and were identified as frequent transit travelers. Clearly, this is a relative measure, but for this study it focuses results on people who use the mode at least once per week. These travelers were then divided into groups based on their change in transit use from pre-pandemic to when the survey was taken (June 2022). The analysis used Pearson's X^2 with Rao and Scott adjustment to identify significant differences between these three groups in Table 4.

The PSS and FCV scores of frequent transit users who used more, the same, or less transit were compared (see Tables 5 and 6). Each category was analyzed using a Pearson's X^2 with Rao and Scott adjustment to identify if there was a significant difference in travelers' PSS or FCV scores based on their stated change in transit use. There were several significant differences, but the key takeaway was that people with higher PSS and FCV scores were more likely to use less transit. The results appear to corroborate the literature reviewed on overall travel and transit use. It appears that people still have some fear of COVID-19 and being inside crowded transit vehicles. These people tend to use more private vehicles, which is one reason why transit travel has not been able to rebound as quickly as highway travel.

Table 4. Change in Transit Use of Frequent Transit Riders

Characteristic		Change in Transit Use: June 2022 Compared to Pre-pandemic (% of Frequent Transit Users)		
		Less	Same	More
*All Frequent Transit Riders***		57.6	32.9	9.5
*Gender***	*Female*	61.9	26.4	11.7
	Male	52.9	40.0	7.1
	Others / No Answer	50.1	33.8	16.1
*Age (years old)**	*18 ~ 24*	61.0	28.5	10.5
	25 ~ 34	42.1	50.1	7.8
	35 ~ 44	59.7	31.0	9.3
	45 ~ 54	53.7	31.7	14.5
	Above 55	69.4	22.9	7.6
*Annual Household Income ($U.S.)***	*Under 15,000*	43.5	45.5	11.0
	15,000 ~ 24,999	47.3	43.7	9.0
	25,000 ~ 34,999	43.2	50.9	5.9
	35,000 ~ 49,999	64.1	20.2	15.7
	50,000 ~ 74,999	65.9	25.8	8.3
	75,000 ~ 99,999	55.8	38.6	5.6
	100,000 ~ 149,999	60.9	32.5	6.6
	More than 150,000	70.0	13.9	16.1
	Prefer not to answer	70.1	14.8	15.1
Ethnicity	White or Caucasian	55.9	34.9	9.2
	Hispanic	65.2	25.3	9.6
	Black or African American	64.1	27.0	8.9
	Asian	49.1	34.6	16.2

Characteristic		Change in Transit Use: June 2022 Compared to Pre-pandemic (% of Frequent Transit Users)		
		Less	Same	More
	Native American or Alaskan Native	56.7	36.3	7.0
	Multiracial or Biracial	47.7	37.3	14.6
	Others	35.4	59.6	5.1
Contracted COVID-19	Yes	54.4	32.2	13.4
	No	57.5	33.6	8.8
	Unsure	63.7	30.5	5.8
	Prefer not to say	39.4	47.4	13.2
Do you own/have access to a motor vehicle?	Yes	49.8	29.7	8.9
	No	7.9	3.1	0.7
		Score		
PSS (max value = 40)		18.91	17.22	17.92
*FCV (max value = 35)**		22.04	18.95	20.96

*Note: *= significant difference at a 5 percent level; ** = significant difference at a 1 percent level.*

Table 5. PSS Scores of Frequent Transit Riders

Characteristic		PSS Score		
		Change in Transit Use in June 2022 Compared to Pre-pandemic		
		Less	Same	More
All Frequent Transit Riders		18.91	17.22	17.92
Gender	Female	19.05	17.48	17.57
	*Male***	18.72	17.01	18.60
	Others	20.74	20.00	19.25
Ethnicity	*White or Caucasian***	17.76	16.56	17.84
	Hispanic	19.51	18.64	16.72
	Black or African American	23.52	19.50	18.56
	Asian	18.90	18.64	18.80

Characteristic		PSS Score		
		Change in Transit Use in June 2022 Compared to Pre-pandemic		
		Less	Same	More
	Native American or Alaskan Native	19.76	18.09	18.78
	Multiracial or Biracial	18.99	20.07	19.33
	Others	21.83	15.18	31.00
Age	*18 ~ 24***	19.74	19.47	19.46
	*25 ~ 34***	19.36	19.26	18.91
	35 ~ 44	18.82	18.05	18.60
	45 ~ 54	17.75	17.50	17.97
	Above 55	19.05	12.27	16.03
Do you own/have access to a motor vehicle?	No	20.65	19.56	18.33
	*Yes***	18.63	16.97	17.89
Income	Under 15,000	20.82	19.76	20.53
	*15,000 ~ 24,999***	19.36	19.25	17.61
	25,000 ~ 34,999	18.88	17.96	18.18
	*35,000 ~ 49,999***	20.45	18.47	16.44
	50,000 ~ 74,999	16.67	17.99	18.15
	75,000 ~ 99,999	20.48	15.09	17.36
	100,000 ~ 149,999	18.45	13.93	19.13
	More than 150,000	16.55	18.28	18.99
	Prefer not to answer	18.35	25.34	21.69

*Note: *= significant difference at a 5 percent level; ** = significant difference at a 1 percent level.*

Table 6. FCV Scores of Frequent Transit Riders

Characteristic		FCV		
		Change in Transit Use		
		Less	Same	More
All Frequent Transit Riders		22.04	18.95	20.96
Gender	*Female***	21.63	18.36	20.52
	*Male***	22.59	19.40	21.83
	Others	20.22	18.00	19.75
Ethnicity	*White or Caucasian***	21.55	18.63	20.92
	*Hispanic**	22.64	20.08	21.54
	Black or African American	23.93	19.89	21.49
	Asian	21.08	18.29	19.36
	Native American or Alaskan Native	23.75	21.67	20.07
	Multiracial or Biracial	20.99	21.30	21.95
	Others	16.69	13.52	17.00
Age	*18 ~ 24***	21.39	18.86	20.17
	*25 ~ 34***	24.62	21.75	22.18
	35 ~ 44	24.70	23.05	24.87
	45 ~ 54	19.20	18.33	19.16
	Above 55	21.06	12.10	19.92
Do you own/have access to a motor vehicle?	No	22.75	18.07	21.50
	*Yes***	21.93	19.03	20.92
Income	Under 15,000	19.42	21.98	19.03
	*15,000 ~ 24,999***	19.55	20.39	19.11
	*25,000 ~ 34,999***	22.98	21.58	22.12
	35,000 ~ 49,999	23.59	18.18	23.72
	50,000 ~ 74,999	20.01	20.73	21.21
	75,000 ~ 99,999	24.72	16.31	20.33
	100,000 ~ 149,999	21.87	14.53	25.37

Characteristic		FCV		
		Change in Transit Use		
		Less	**Same**	**More**
	More than 150,000	20.51	22.51	14.89
	Prefer not to answer	17.67	15.23	12.80

Next, the importance of the factors behind the respondents' use of a motor vehicle was examined (see Figure 19). To begin, 28% of the respondents who owned a vehicle indicated pandemic related factors, such as lower chance of catching the virus, were an extremely important factor for their choosing to use a motor vehicle. To understand the challenges faced by the individuals while using transit, all participants were asked to select the key barriers that prevented them from using transit more often. The respondents could choose a maximum of three factors. Fear of catching the virus was the most chosen obstacle, with 36% of respondents choosing it (see Figure 20). Owning a vehicle and long waiting times were also some of the major obstacles to transit use chosen by the respondents.

The respondents who changed their transit ridership from at least once a week before the onset of COVID-19 to never or once a month were asked about the likelihood of their return to transit given specific changes (see Figure 21). Twenty-five percent of these respondents were extremely likely to return to transit again if most of the population received a vaccination. Figure 22 shows the percentage distribution of respondents' comfort level if they were to experience the same environment of that crowded bus stop and bus ride as shown in the video. The results show that 12% of the respondents were extremely uncomfortable if they were to experience a crowded bus stop as shown in the video. Similarly, 18% of the respondents were extremely uncomfortable if they were to experience a crowded bus ride as shown in the video. These results, along with several other analyses, show that COVID-19 is still a significant deterrent to transit use. The overall impact, based on all our analysis, is summarized in Chapter 7.

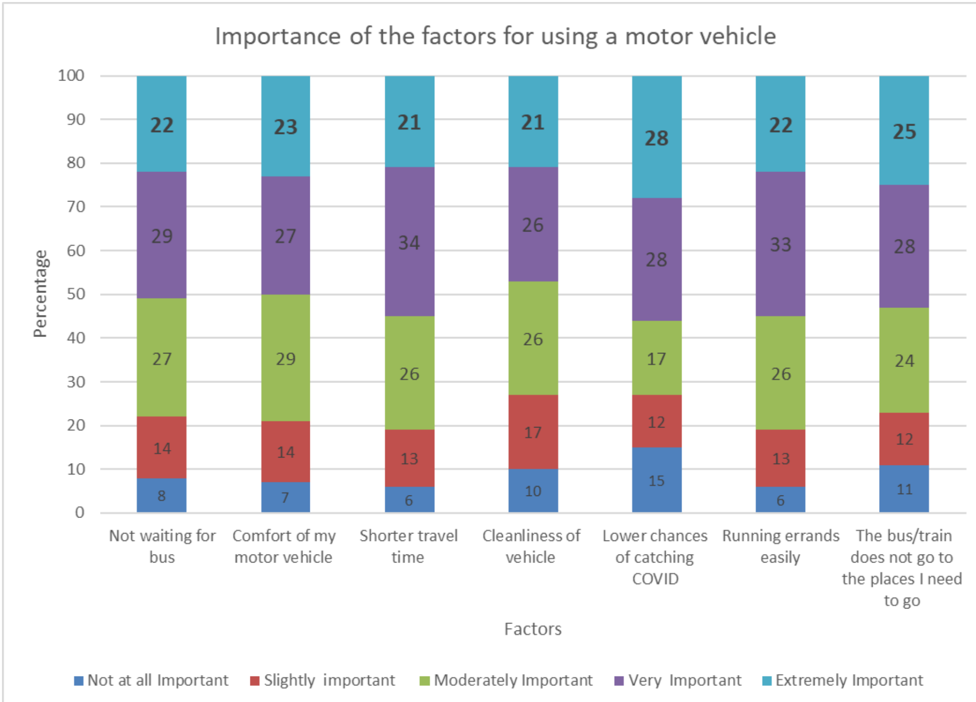


Figure 19. Importance of the Factors for Using a Motor Vehicle

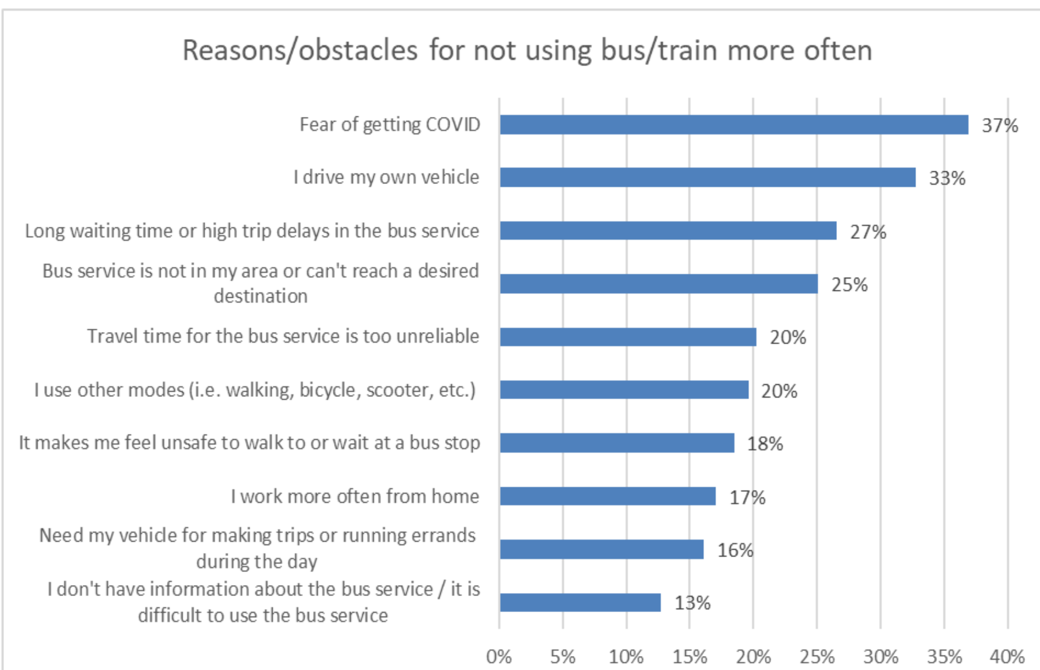


Figure 20. Factors Responsible for Not Using Transit More Often

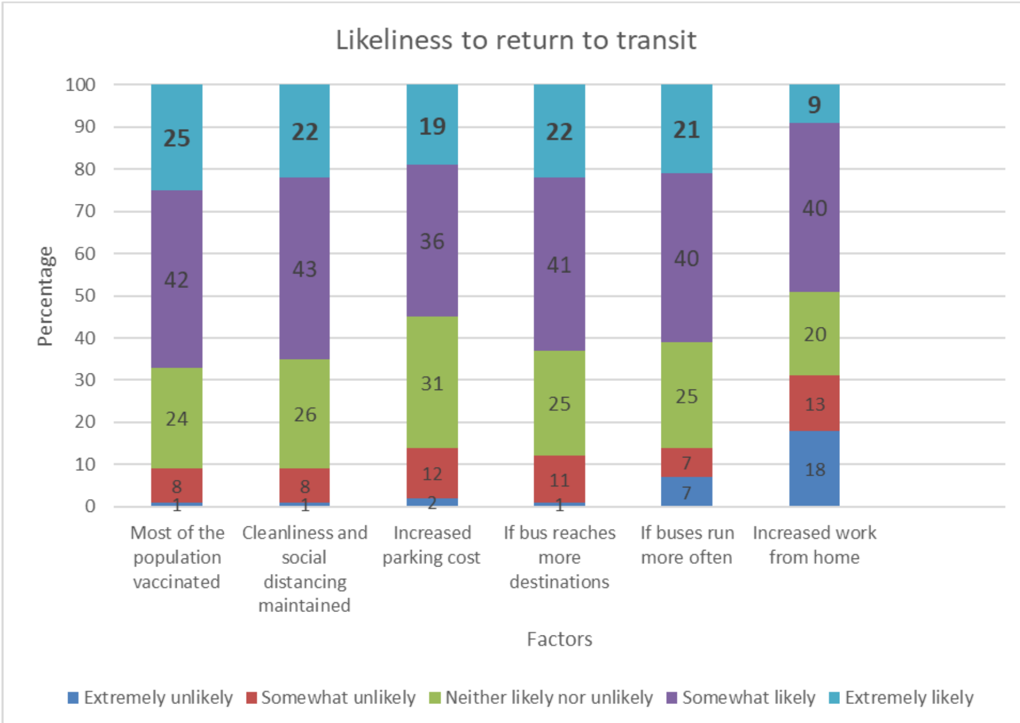


Figure 21. Likeliness to Return to Transit Given Different Scenarios

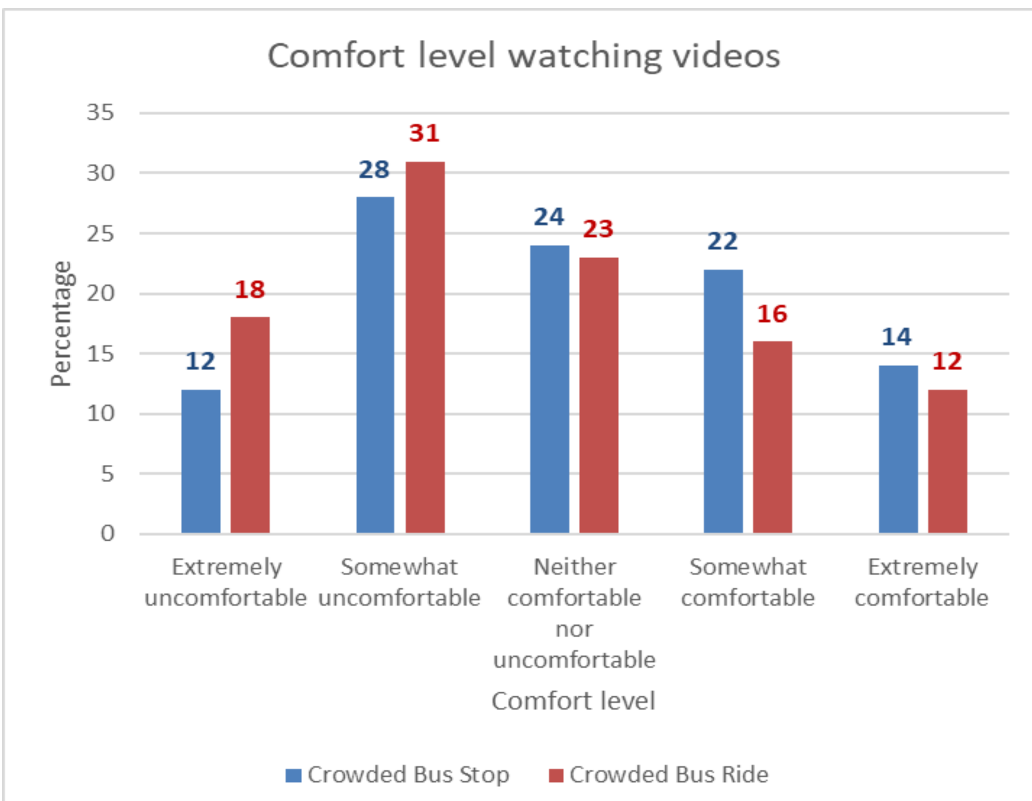


Figure 22. Percentage Distribution of Respondents' Stated Comfort Level

Validity of the Virtual Bus Experience

An important part of the survey was how the respondents would react to the virtual bus experience (the first-person videos of a crowded bus and crowded bus stop) that was embedded in the survey. An important check on the overall investigation is that the experiences subjects encounter in the simulated/virtual bus experience have some predictive value in their behavior. We posit that self-reported feelings of comfort in the virtual bus provide additional explanatory power beyond typical survey measures on attitudes toward transit in general.

We begin our approach using a factor analysis of survey responses to gauge general attitudes toward transit based on the respondents' change in use of transit. Our analysis yields four factors that we name COVID fear, patience, access to private auto, and fulltime. Table 7 provides the factor loadings for each factor in a rotated, normalized loading. The first factor, coined “COVID fear,” concerns responses to the “COVID fear” questions, the questions examining respondents’ uneasiness with COVID-19, certain responses to questions “obstacles to using transit” and “reasons for private auto” concerning COVID-19 are also included. It is also correlated with full time workers and negatively correlated with being a student. The second factor, named “patience” is strongly negatively correlated with those who do not use transit due to wait times. It is positively correlated with higher age, more people in the household, and various non-white ethnicities. The third factor, named “access to private auto” is positively correlated with subject responses to “reasons for private auto” questions about the relative importance of private transportation, it is correlated with white ethnicity, income, and full-time work. The fourth factor is named “fulltime”. It is positively correlated with educational attainment and full-time work and negatively correlated with part time work and being a student.

We use these four factors as representative of typical traffic survey responses. We examine their effectiveness at predicting the COVID-19 drop off in transit use, specifically the differences in responses to the questions “Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train?” and “Currently, how often do you ride the bus/train?”. On both questions, subjects could respond at six levels of frequency. Forty-four percent of subjects did not change their response between questions, 34% decreased their usage and 21% increased their usage. The numerical average of the responses is a drop of 0.166 levels between questions.

Table 7. Factors Relevant to Change in Transit Use

Question	f1: COVID fear	f2: patience	f3: private auto	f4: full time
Obstacles to using transport:				
I work more often from home				
Bus service not in area				
Travel time is unreliable				
Need (personal) vehicle for other reasons				
Fear of getting COVID	0.36			
Bus stop is unsafe				
Long waiting time or high trip delays		-0.40		
I don't have information about transit service				
I drive my own vehicle			0.28	
I use other modes of transport				
Importance of factors of personal motor vehicle:				
I don't have to wait for the bus			0.32	
Comfort			0.33	
Shorter travel time			0.35	
Cleanliness of vehicle			0.30	
Lower chances of catching COVID	0.35		0.28	
Can run errands/shopping at any time			0.34	
The bus/train does not go to the places I need to go			0.34	
Age		0.52		
Ethnicity:				
Hispanic or Latino			0.30	
Asian or Pacific Islander		0.26		
White or Caucasian		-0.82		
Black or African American		0.31		
Native American or Alaskan Native		0.31		

Question	f1: COVID fear	f2: patience	f3: private auto	f4: full time
Multiracial or Biracial		0.28		
Not listed				
Gender: Male		-0.26		
Education level (1–6)				0.36
Work status:				
Employed full-time	0.30	-0.39		0.73
Employed part-time				-0.72
Student	-0.39		0.41	-0.31
Retired				
Homemaker				
Unemployed				
Days working from home prior to March 2020				
Tested positive for COVID				
Income level (1–11)			0.39	
People in household		0.48		
Psychological Control:				
How often are you upset?				
How often are you unable to control?				
How often are you nervous and stressed?				
Unable to handle personal problems?				
Felt things were going your way?				
Could not cope with required tasks?				
Unable to control irritations?				
On top of things?				
Angered by things outside your control?				
Unable to control difficulties?				
COVID fear:				

Question	f1: COVID fear	f2: patience	f3: private auto	f4: full time
Afraid of COVID (1–5)?	0.56			
Uncomfortable to think of COVID (1–5)?	0.58			
Hands become clammy when thinking of COVID (1–5)?	0.55			
Afraid of losing my life because of COVID (1–5)?	0.58			
Nervous or anxious about COVID news (1–5)?	0.54			
Losing sleep because of COVID (1–5)?	0.52			
Heart races or palpitates when I think of COVID (1–5)?	0.59			

Notes: Factors chosen with eigenvalues above 1.5, normalized and rotated. Only values with correlations above abs (0.25) shown in table.

We regress the difference and incidence of drop on the four factors as well as subject self-report uneasiness to the bus videos. The regressions are weighted to be representative of the U.S. population (though other weightings to not change the general themes presented here). The results are illuminating (see Table 8). A standard deviation change in COVID fear is associated with a 0.4 drop in levels between questions and a 15-percentage point increased likelihood of reducing transport use. The factor patience is not statistically meaningful on either measure. Access to private auto is associated with a 0.15-point drop in levels and a 5-percentage point increased likelihood of an overall reduction in transit use. Full-time work is also associated with a 0.30-point drop in levels and a 10-percentage point increase in the likelihood of reduced transit use. Despite all this explanatory power, self-reported uneasiness to the videos has additional explanatory power. While uneasiness expressed at the bus stop does not have a statistically meaningful impact on results, a single level increase in comfort (out of five levels of comfort) is associated with a 0.16-point drop in levels and 10 percentage point drop in likelihood of reducing transit use.

Table 8. Impact on Transit Use by Factors

Variables	(1) Transport Frequency Change	(2) Transport Direction Change
f1: COVID fear	0.411*** (0.084)	0.155*** (0.026)
f2: patience	0.049 (0.082)	0.014 (0.030)
f3: private auto	0.147** (0.064)	0.051* (0.029)
f4: full time	0.315*** (0.066)	0.103*** (0.028)

Variables	(1) Transport Frequency Change	(2) Transport Direction Change
Bus stop video comfort	0.065 (0.053)	0.022 (0.024)
Bus riding video comfort	-0.161** (0.070)	-0.107*** (0.030)
Constant	0.502** (0.248)	0.419*** (0.092)
Observations[1]	5.588	5.588
Population size	296,456,428	296,456,428
R^2	0.1133	0.0957

(1) This is not the full 6,300 responses as anyone not answering each question was removed from this analysis.

Models of Transit Use

This section presents the results from a modeling analysis of the survey responses obtained from frequent transit users aimed to identify factors that could explain their current and future use of transit. Frequent users were defined in the survey as any person who stated using transit at least one time or more per week. The responses were coded as a binary variable to identify people whose transit use increased or remained the same versus those who decreased their use from before the pandemic. The group that decreased their transit use consisted of 57.4% of the sample.

Discrete and categorical responses were converted to binary variables. An example of the coding used is presented with survey question 2.6: "*Select all of the following reasons or obstacles that keep you from using the bus/train more often.*" This question asked the importance of several factors, such as fear of COVID-19 and vehicle ownership, among others, that prevented a person from using transit. A binary variable was created for all the response options available. If the person selected any of the factors as important to their decision, that response was assigned a value of one (1). If not, that factor was assigned a value of zero (0).

As the response variable was binary (either the person decreased transit use or not), a classification model was proposed. The main intention of the model was to find which variables have the greatest impact in the respondent's decision to use transit. There are multiple classification approaches such as Logistic Regression, Naive Bayes, Decision Trees, and more. Logistic Regression was not selected due to limitations with non-linear data. A Decision Tree model was selected as it accounts for feature interactions in the splits (decision boundaries) while being relatively easy to interpret. Also, recent applications of game theory allow us to dismantle black boxes such as tree ensemble methods and overcome heuristic and not individualized feature attribution techniques (Lundberg et al., 2019). Ensemble learning trains multiple models on the same data to compose a final prediction and boost performance. Random Forests (RF) are a combination of tree predictors. Decision Trees work by choosing the most important feature as root and start doing partitions that subdivides predictor space into internal nodes. Each internal node represents a test on the feature, and each branch (segments of the tree that connects nodes) is denoted by the outcome of the test. The final regions are known as terminal nodes or leaves of the tree, more commonly known as classes or labels (James et al., 2013).

The random term in RF comes from the random selection of features to split each node. There are multiple ways to produce the randomness of the forest, but all have in common that for the *k-th* tree, a random vector is generated Θ_k independent of the previous random vectors $\Theta_1, \ldots, \Theta_{k-1}$ but with the same distribution (Breiman, 2001). Once the large number of trees are generated, they proceed to vote for the most popular class outputted in the terminal nodes. Breiman's approach is the original version of RF, where each tree is trained on a bootstrap sample drawn randomly from the data. It uses Decrease Gini Impurity (DGI) and CART method as the splitting criterion. The package *scikit-learn* was used for this analysis (Pedregosa et al., 2011). The data was divided in training and testing sets, by 70% and 30%, respectively. A RF was trained with default parameters resulting in 69.2% accuracy and 71.1% F1-Score on the testing data. Note this was based on unweighted data since weighting the data was not an available option for these analysis techniques.

After reviewing the model performance, an analysis of how each variable or feature affects the model prediction was performed to understand what are the factors that influenced users to increase or decrease using transit. A feature importance was calculated by the package *scikit learn* based on DGI criteria. In the Decision Tree discussion, it was mentioned how they are a set of internal nodes and final leaves. For each internal node, a selected feature is used to mark a decision boundary by splitting the data into two separate sets. These features are selected with criterion, and for classification tasks that is where the Gini impurity comes into play. Information gain is another criterion widely used to select the features. The purpose of DGI is measuring how each feature decreases the impurity of the split (Breiman, 2001). Afterwards, an average is calculated over all trees and is accounted as Feature Importance. The Gini Index is defined as the measure of total variance across all *K* classes with equation 1:

$$G = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk}), \tag{1}$$

where $\hat{p}_{mk}$ represents the proportion of training observations in the *m-th* region from the *k-th* class. If all the $\hat{p}_{mk}$ are close to zero or one, the Gini Index will take a small value.

Consequently, that is why it is referred to as a measure of node purity; a small value indicates that a node contains predominantly observations from a single class (James et al., 2013). The Feature Importance based on DGI was calculated for the RF and is shown in Figure 23. The Confusion Matrix (CF) summarizes the performance of the algorithm indicating the model had 71% of correct predictions in Group 1 (Increased/same transit use) and 67% correct predictions in Group 0 (Decreased transit use).

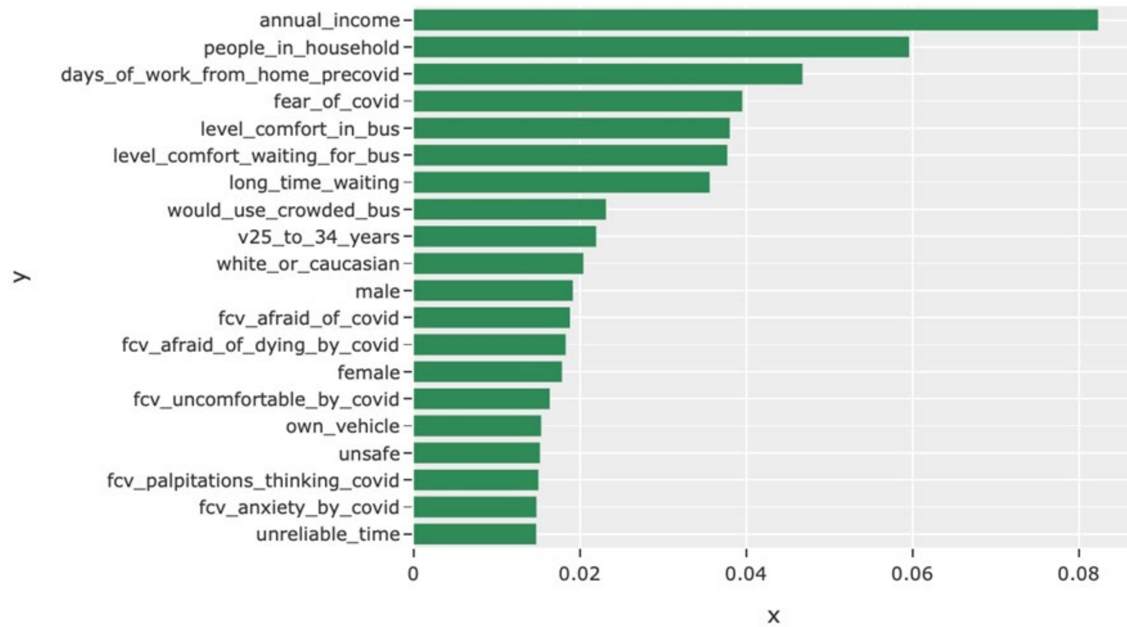


Figure 23. DGI Feature Importance of Transit Use During COVID-19

The twenty most important features to explain the stated reduced use of transit during COVID-19 are shown on Figure 23. The list of variables is shown in descending order with those with the highest importance at the top. The top five variables were the annual income, people in the household, days teleworking before the pandemic, the fear of COVID-19, and the comfort level when inside a crowded bus.

The information generated from DGI does not explain how each variable contributes uniquely to the final prediction or terminal node. SHAP (Shapley Additive Explanation) values are recommended by Lundberg et al. (2019) as the only consistent and locally accurate individualized feature attributions. For the scope of this analysis, the implementation was conducted with the SHAP Python package explained by Lundberg et al. (2019).

There are multiple ways to visualize and see how each feature contributes to the predicted class with the SHAP object. The SHAP Value plot in Figure 24 shows the positive and negative relationships of features with the response variable use of transit during COVID-19. The plot is constituted by the four main characteristics: feature importance, impact, feature value, and correlation. Feature importance is seen as each variable is graphed and ranked in a descending order. For the impact, the x-axis shows whether specific features values are associated with a higher or lower prediction. Feature values go from low to high, being indicated by the color of the point. Each point represents an instance in the data set. For binary variables, a green color represents a value of zero (low) and a yellow color a value of one (high).

The plot also considers correlation by combining the x-axis and feature values. For instance, the SHAP value plot in Figure 24 shows how a lower income has a significant positive impact on the model output. As the green colored points for the income variable are shown on the right side of the x axis it represents that people with a lower salary are more likely to have increased or have the same level of transit use than before COVID-19.

The annual household income variable has the highest feature importance in the SHAP plot. The trend of lighter color dots on the negative side of the x-axis indicates that people with higher incomes stated to decrease their use of transit during the pandemic.

The Fear of COVID-19 (FCV) variable has the second highest feature importance. This variable tends to indicate that people that identified the disease as an important factor in their decision to decrease their use of transit is confirmed by the lighter color dots in the negative side of the x-axis.

The next three variables with higher feature importance are the number of people in the household, long time waiting, and the number of days working from home before the pandemic. The SHAP plot shows that persons from smaller households, those who selected long waiting times as a factor for not using transit, and those working more days from home before the pandemic reduced their transit use during the pandemic.

The second tier of variables of feature importance include two statements from the FCV instrument (“afraid of COVID-19” and “afraid of dying of COVID-19”), the level of comfort inside a crowded bus, along with 25-to-34 years old and male individuals. Those persons that stated to agree with the two FCV-19S statements, those persons not being comfortable inside a crowded bus, and those not from the 25-to-34 years old and male groups reduced their transit use during the pandemic.

To confirm the relationships observed in the SHAP Value Plot, histograms for the fear of COVID-19, annual income, people that use their own motor vehicle for lower COVID-19 risk, and education level variables are shown in Figure 25.

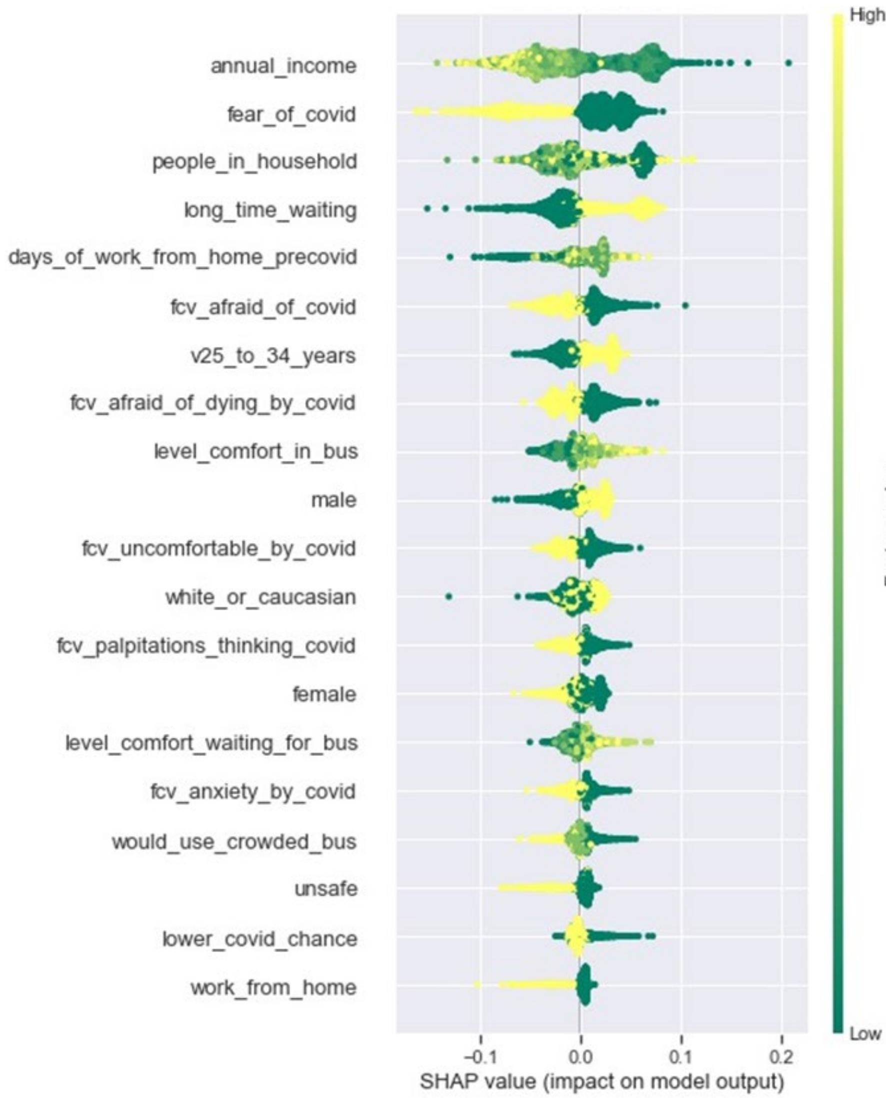
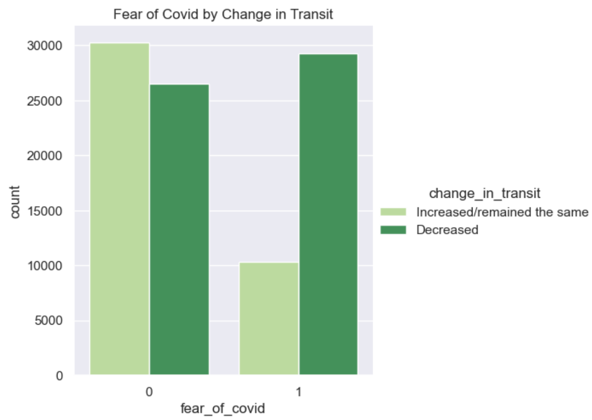
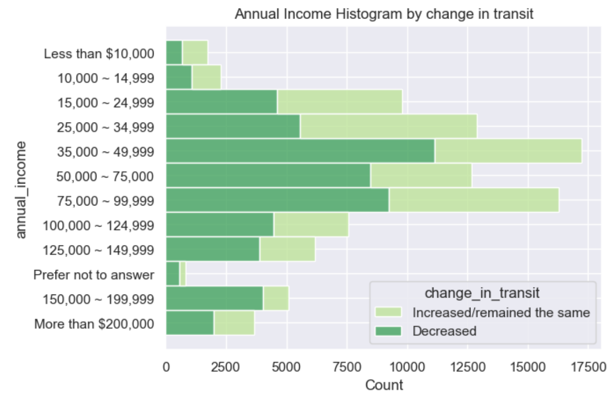


Figure 24. SHAP Value Plot for the Stated Transit Use During COVID-19

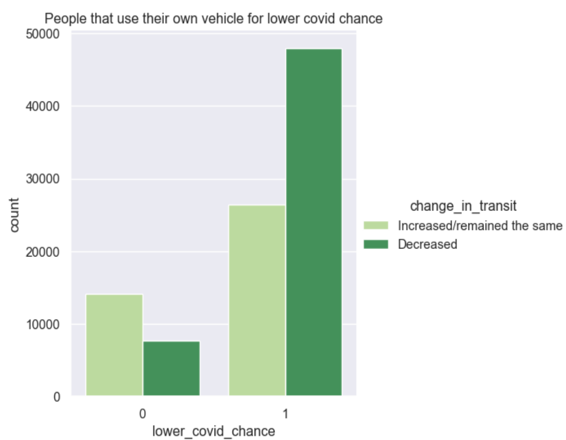
The fear of COVID-19 variable indicates that most of the respondents that identified the factor as important in their decision to select transit (value of one in Figure 25a) decreased their use of transit during the pandemic. The annual income (Figure 25b) shows that people with lower incomes (less than $35,000) tend to use more transit. As the income is higher, the use of transit tends to decrease significantly. Respondents that stated to use their own motor vehicle because of a lower risk of getting COVID-19 (value of one in Figure 25c) decreased their transit use, compared to the people who did not state that factor was important. The education level variable (in Figure 25d) shows that the decrease of transit use during COVID-19 was somewhat higher for those persons that completed a bachelor or a graduate college degree.



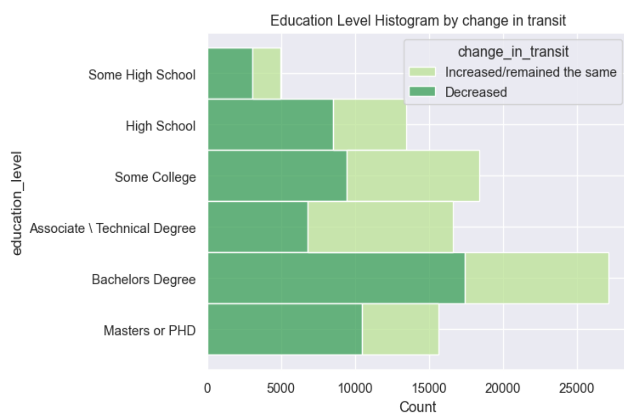
(a) Fear of COVID-19



(b) Annual income



(c) People that use private motor vehicle



(d) Education level

Figure 25. Relationships between Feature Attribution and Stated Transit Use During COVID-19

A similar analysis using the RF model and the SHAP plot was conducted using the responses for the stated future use of transit (question 2.4 in the survey). As with the previous model, the sample of frequent transit users was used. In the second model, the response variable assessed the decision of using transit once the pandemic is no longer a threat: either reduced their use of transit (taking a value of zero) or it will increase or remain the same (taking a value of one). The objective of the analysis was to identify factors that explain if the survey respondents will return to transit once the pandemic is no longer perceived as a threat.

The Feature Importance based on DGI was calculated for the second RF and is shown in Figure 26. The Confusion Matrix (CF) indicates the model had 70% of correct predictions in Group 1 (Increased/same transit use) and 69% correct predictions in Group 0 (Decreased transit use).

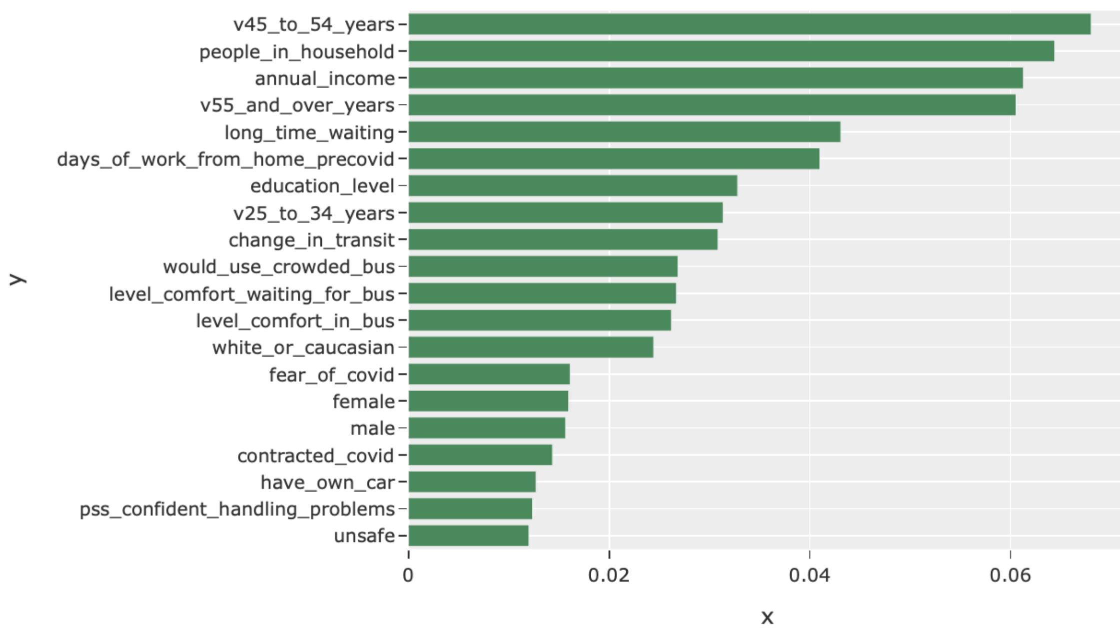


Figure 26. DGI Feature Importance of Transit Use After COVID-19

The 20 most important features to explain the stated use of transit after COVID-19 are shown in the figure. The top five variables for the use of transit after COVID-19 were the people in the 45 to 54 age group and the 55 and older group, people in the household, annual income, and people that selected long waiting times as factors for not using transit. The fear of COVID and the level of comfort in crowded bus variables, which were very important as factors for the use of transit during COVID-19, have much less importance in the response for the future use of transit. In contrast, the two age groups were not included in the top list of factors for transit use during COVID-19.

The SHAP Value plot in Figure 27 shows the positive and negative relationships of features with the response variable use of transit after COVID-19. The green color represents a value of zero (low) and a yellow color a value of one (high).

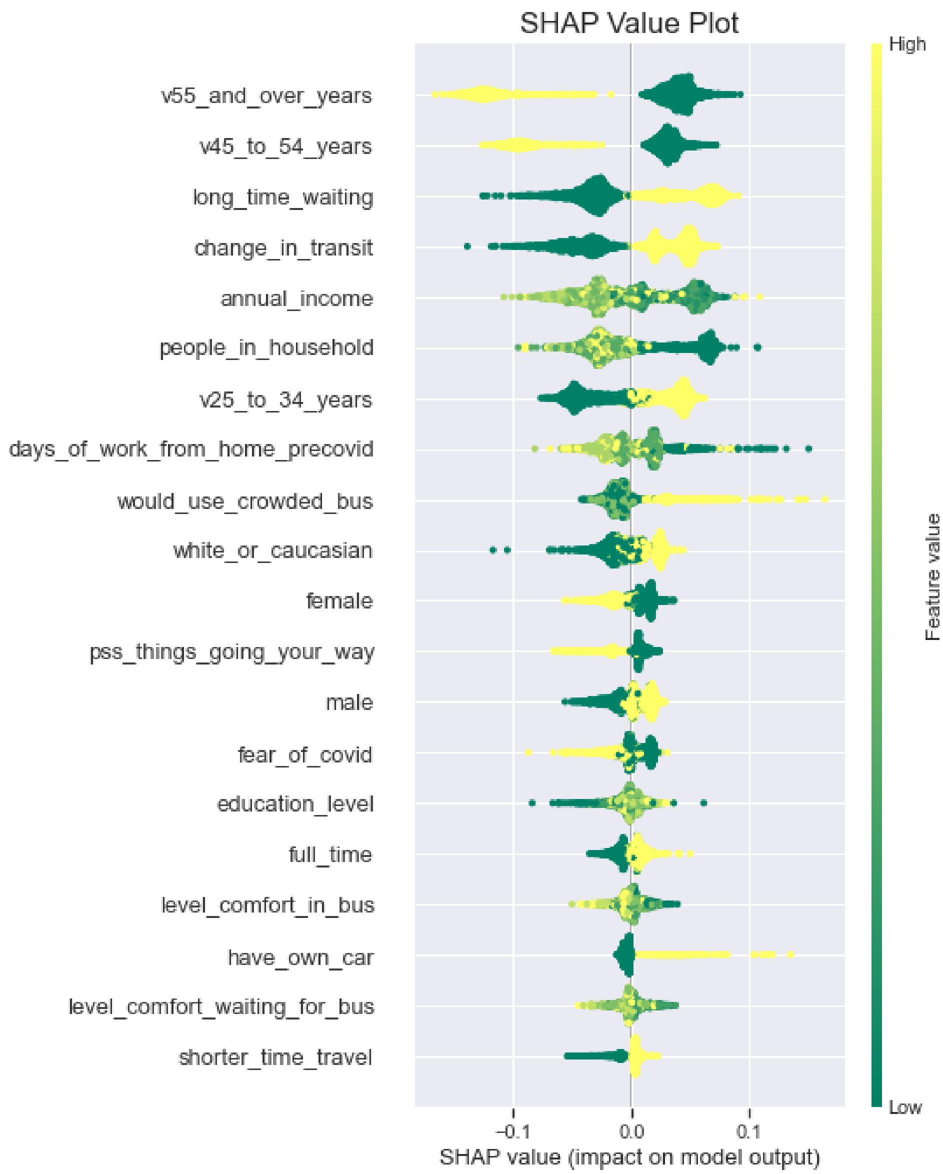


Figure 27. SHAP Value Plot for the Stated Transit Use After COVID-19

Two age categories resulted with the top two feature importance in the SHAP plot. The trend of yellow color dots on the negative side of the x-axis for the two categorical variables indicates that people in those two age groups will decrease their use of transit after the pandemic.

The next three variables with higher feature importance are long time waiting, change in transit use, and annual income. The SHAP plot shows that persons who selected long waiting times as a factor for not using transit, that reduced their use of transit during the pandemic, and have lower annual incomes will use transit more after the pandemic is over.

In summary, the SHAP plot values are representative of the data behavior and the split that were made on features with the most importance in final predictions. There is a strong indication that COVID-19 related variables have an impact and influence on a user deciding whether to use public transportation or not.

Summary of Web Survey Results

Transit ridership has not yet rebounded to pre-pandemic levels. A survey was conducted of the travelers' stated use of transit before, during, and after the pandemic to identify how factors associated with the stress level and fear of COVID-19 may be impacting transit use. About 41% of the survey respondents stated to have reduced their use of transit after the pandemic declaration in March 2020. Respondents who stated a lower use of transit also correspond to those with higher stress levels and fear of COVID-19 from the standardized PSS and FCV instruments.

Some respondents stated uncomfortableness if experiencing the same environment as shown in the first-perspective videos and some citied COVID-19 as major reason to not use transit more often or as a major reason to use motor vehicle. Depending on which answers are used there may be as many as 35% to 45% of respondents who will not use transit as much in the future due to COVID-19. This higher range occurs if both the responses “Extremely” and “Very” are considered indicators of future travel decisions for survey questions asking the importance or likeliness of COVID-19 factors in determining that respondents future transit use. However, if we consider only those respondents who indicated “Extremely Important,” “Extremely Likely,” and “Extremely Uncomfortable,” then a lower range of approximately 15% to 25% of the respondents will not use transit as much in the future due to COVID-19.

A Random Forest classification model and a SHAP Value Plot were developed to identify factors that could explain the stated reduced transit use of frequent travelers. The most important factors that were related to decrease in transit use are:

- Larger household size
- High fear of getting COVID-19 on transit and in general
- High annual income
- Preference for shorter waiting times
- Working from home

Although structural and operational changes are necessary to mitigate travel changes due to working from home and mode shift, transit agencies must also focus strategies on measures directed to gain confidence in travelers to reduce stress factors related to COVID-19. People tend to have greater FCV scores when they choose to use less public transit, which reveals that the impact of COVID-19 influences people's willingness to travel using public transportation.

Chapter 6. Travel Survey Augmented With GSR

Self-reporting psychological traits and self-reported fear in a web survey could sometimes be misleading as the answers could depend on situations that the respondent is in that have nothing to do with transit use. While there have been studies that have explored transit use post pandemic, the addition of an instrument measuring the neuropsychological state along with a survey to understand travel behavior has not been adequately explored in the literature. To better understand and validate the cognitive impact and stress of COVID-19 in a collective transport system like transit, a psychometric measurement tool along with the survey could give better results.

The Galvanic Skin Response (GSR) device measures physiological characteristics like anxiety and stress due to the change in electrical properties of the skin's moisture level (Sharma et al., 2016). Sweat glands are controlled by the sympathetic nervous system, which causes this phenomenon, thus indirectly indicating mental activity (Vijaya and Shivakumar, 2013). A study used the combination of GSR and survey to find the stress level of drivers in a complex urban traffic situation and found that the GSR results were consistent with the survey results (Dogan et al., 2019). Another study found that the respondents showed a higher stress level in GSR, imagining themselves while watching the first-person perspective video of them getting hurt (Hagni et al., 2008). This tool was also used in a clinical context to find anxiety in children before a dental visit (Najafpour et al., 2017). A research study that employed GSR to assess visual strain while watching 3D and 2D displays discovered that stress increased when viewing 3D videos from a closer distance than when seeing 2D videos (Ramadan and Alhaag, 2018). These studies indicate that GSR is an effective tool in depicting stress levels among individuals.

Web surveys face the challenge of low data quality as participants often answer quickly, making it impossible to verify whether the response is honest. Measuring self-reported fear/stress through a web survey might not show consistent results with an individual's actual psychological factors. This phase of the study aims to answer these questions by including psychological scales in the survey and instruments like Galvanic Skin Response (GSR) to better understand the travel choices as respondents answer a survey. This phase of the research study tried to minimize the low data quality by inviting participants to a lab and conducting the study on the lab's computer. To better validate the measure of the participant's stress levels and the consistency of the responses to the survey, the GSR meter was used. Traveler's stress levels during the survey were measured using GSR and facial expression, along with self-reported responses to the survey. This is expected to provide additional insight into the reasons why many travelers have not returned to transit.

Experimental Design

The first part of the design included the development of the travel survey. The questionnaire was the same as the survey discussed in the previous section of the report except it had four additional paid questions in addition to the same set of questions as the web survey. The additional paid questions aimed to ensure the participants were attentive while watching the first-person videos of transit use. The survey included 44 questions.

As the survey aimed to find self-reported fear/stress, the experimental design included a device (GSR) measuring the neuropsychological state to better understand/judge the individuals' stress/fear. To understand the true reflection of human behavior, real-time data about the fear/stress of COVID-19 on the subjects while watching the first-perspective videos and responding to the survey was collected. The design setup included inviting the participants to the laboratory where they answered the survey questions on the lab's computers with the GSR equipment attached to their fingers recording their skin conductance. The setup included a webcam to record the subject's facial expressions. Both this phase of the study and the web survey phase required and obtained Institutional Review Board (IRB) approval.

Data Collection

The research was conducted at the Human Behavior Laboratory at Texas A&M University. The subject group included Texas A&M students above 18 years of age. The subjects were recruited through an advertisement email sent to the university listserv and the human behavior laboratory subject pool system, SONA. The advertisement email provided information about the study's objective, compensation, and the potential risks involved. The interested participants signed up for the study through the link provided in the email and chose the available time slots. On arrival, the participants provided their consent to the study and were directed to the computer lab where the GSR device was attached to their index fingers. After finishing the survey, each of the subjects was paid a monetary show-up fee with additional earnings depending on the number of correct questions they answered. The earnings ranged from $16 to $20, and averaged $19.

The study was conducted over the course of three weeks in the months of June and July 2022 and 235 respondents took part in the study. The data was collected in Qualtrics and iMotions. The Qualtrics software collected the survey responses for each participant whereas the iMotions was used to retrieve the video data containing each participant's skin conductance (measuring stress peaks), facial expressions, and the on-screen survey response. Figures 28 and 29 show the image of the experiment and the snapshot of video data collection using iMotions software respectively.

Figure 28. Survey Environment at the HBL Lab

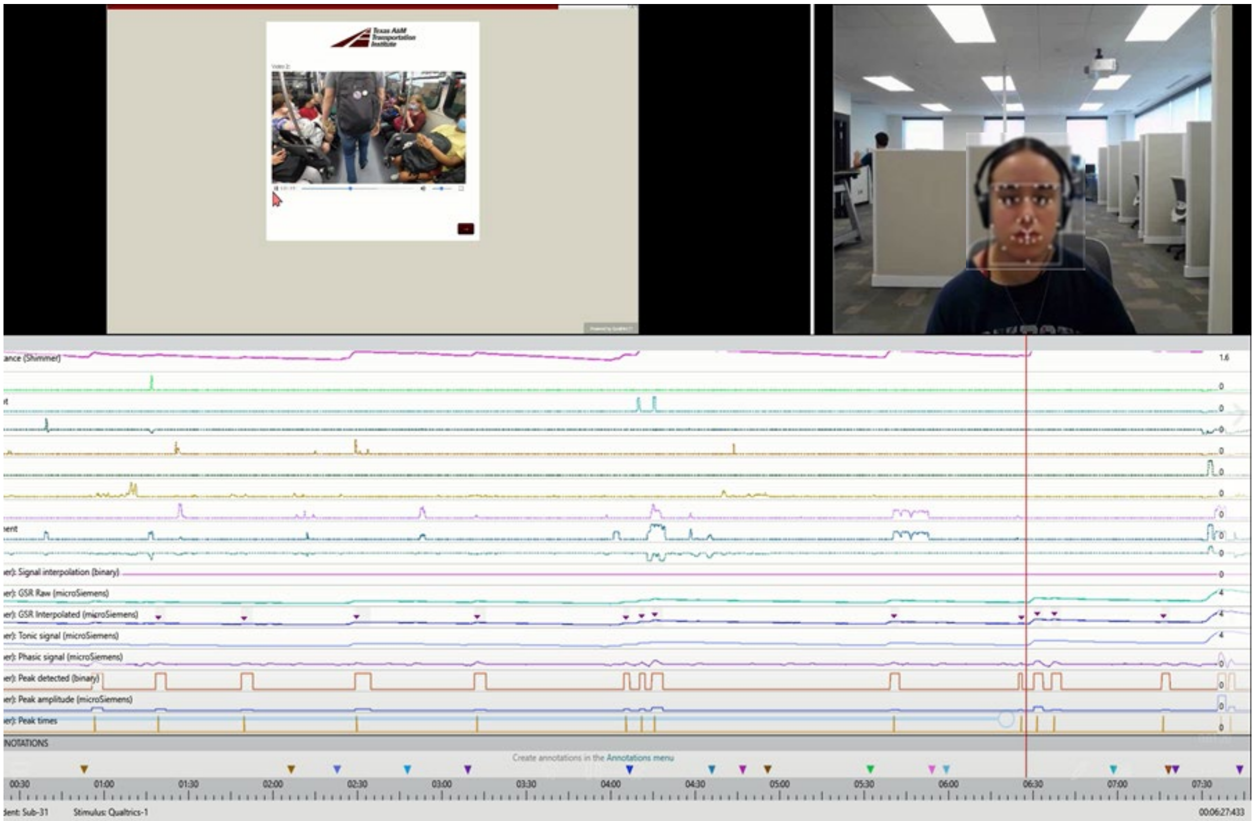


Figure 29. Example of Video Data Collected by iMotions

Analysis

Data from multiple sources (survey responses, GSR skin conductance, and facial expressions) were collected for each respondent. Survey responses were collected in the Qualtrics software whereas the videos containing the facial expression and GSR peaks were collected in the iMotions software. However, a single file representing all the data for everyone was required for the analysis. The data were combined into a single excel file. The GSR peaks had a delay of 2–3 seconds after the respondent was stressed, so to find out the reason for the peak, the question the respondent was on 2–3 seconds before the peak was noted as the potential reason for the peak. The videos were scrutinized to ensure the peaks due to physical movements were ignored. A new column beside each question was created. If a respondent had a peak due to a particular question, the new column was populated with 1, else it was 0.

The next step in the analysis included the removal of bad/irrelevant data to aim for accurate results. For the data cleaning, two criteria were considered. In the first criterion, it was decided to remove the survey responses that were incomplete or were completed in a duration of fewer than 180 seconds. The survey data did not contain any of the responses meeting the above-mentioned criteria for removal. Another criterion for data cleaning was bad GSR peak data. Due to the noise in the GSR peak readings, the physical activity producing several peaks, the malfunctioning GSR device, and the abrupt closure of the iMotions software, some of the subjects had poor peak data or no peak data at all. Responses containing bad peak data due to noise (19 responses), physical activity (12 responses), and malfunction of GSR and iMotions software (3 responses) were removed from the analysis. One of the individuals completed the study twice, so the data related to the subject's second attempt was also eliminated. A total of 35 responses were removed, resulting in a cleaned sample of 200 respondents for the analysis.

Initial Analysis

The next step in the analysis includes analyzing the cleaned data. Some of the initial analysis includes descriptive analysis as shown in Table 9. These responses are from Texas A&M students and are therefore not representative of all travelers and there was no weighting of the data.

Also, the findings from the fear of COVID questions (FCV-19S scale) were documented and validated in the initial stages of the COVID-19 pandemic. In this part of our research our subjects were college students, and this was well after the start of the pandemic. Therefore, it was important to validate the FCV-19S instrument for our target group. The methodology and the results for the validation of the scale are shown in Appendix C. The overall results showed the scale to have moderate to good internal consistency reliability and a significant one-factor solution. This analysis bolstered the findings of using this scale in the travel behavior survey for our college student sample.

A large group of respondents claimed to use transit less or the same amount compared to the past (46% used transit less and 22.5% the same). In addition, 22.5% of participants stated that they will use less transit in the future, indicating the willingness to use transit after COVID-19 has not recovered to pre-pandemic levels. All these findings are consistent with the previous literature on overall travel and transit use.

Table 9. Sociodemographic Characteristics and Stated Use of Transit

Characteristics		N	% Percent
Age Group	**18 to 24**	137	68.5
	25 to 34	60	30
	35 to 44	2	1
	45 to 54	1	0.5
Ethnicity	**Asian**	91	45.5
	Black or African American	9	4.5
	Hispanic	24	12
	Multiracial or Biracial	6	3
	White or Caucasian	70	35
Sex	**Female**	119	59.5
	Male	81	40.5
Education	**High School**	16	8
	Some College	76	38

Characteristics		N	% Percent
	Associate \ Vocational \ Technical Degree	7	3.5
	Bachelor's Degree	52	26
	Master's or PHD	49	24.5
Job Status	Full-Time	6	3
	Part-Time	49	24.5
	Student	142	71
	Unemployed	3	1.5
Number of days working from home in a week prior to COVID-19	0 days	148	74
	1–2 days	29	14.5
	3–4 days	5	2.5
	5 days	11	5.5
	6–7 days	7	3.5
Number of days working from home in a week	0 days	32	58.2
	1–2 days	11	20
	3–4 days	6	10.9
	5 days	3	5.4
	6–7 days	3	5.5
Contracted COVID?	No	89	44.5
	Unsure	18	9
	Yes	93	46.5
Income	Less than $15,000	58	29
	$15,000 to $24,999	23	11.5
	$25,000 to $34,999	22	11
	$35,000 to $49,999	22	11
	$50,000 to $75,000	14	7
	$75,000 to $99,999	10	5
	$100,000 to $149,999	20	10
	More than $150,000	14	7

Characteristics		N	% Percent
	Prefer not to answer	17	8.5
Number of Household members	1	53	26.5
	2	30	15
	3	30	15
	4	64	32
	More than 4	23	11.5
Do you own or have access to a motor vehicle?	Yes	157	78.5
	No	43	21.5
How often did you ride the bus/train (Past)?	Never	35	17.5
	Less than 1 trip a month	22	11
	1 to 4 trips a month	34	17
	1 to 5 trips a week	39	19.5
	6 to 10 trips a week	40	20
	More than 10 trips a week	30	15
How often do you ride the bus/train?	Never	17	8.5
	Less than 1 trip a month	38	19
	1 to 4 trips a month	36	18
	1 to 5 trips a week	48	24
	6 to 10 trips a week	32	16
	More than 10 trips a week	29	14.5
After COVID-19, will you ride transit more, less, or the same amount as before COVID-19?	Less	45	22.5
	More	51	25.5
	Same	104	52
Do you now ride transit more, less, or the same amount as before COVID-19?	Less	92	46
	More	63	31.5
	Same	45	22.5
Peak	Respondents with no peak	76	38
	Respondents with at least one peak	124	62

These travelers were then divided into groups based on their change in transit use (see Table 10) from pre-pandemic to when the study was conducted (July 2022). The analysis identified significant differences between these three groups. The Chi-Square test was used to determine the significant differences in transit use by categorical variable.

To find the questions which contributed to the major peaks among respondents, the total of each question's peak was counted. The questions that caused a peak (stress) in at least 5% of the total respondents were considered to find their significance in the change in ridership. The questions and the respective number of peaks for each is shown in Figure 30. Both the first-person perspective videos of a crowded bus stop and a crowded bus ride stressed 34% and 39% of respondents, respectively. The other questions which stressed the most respondents were the paid questions. These paid questions were linked to the videos, which shows that participants were stressed about the $4 they could earn by answering the four questions correctly. Approximately 48% of the respondents reported a stress peak when answering at least one of the paid questions. The GSR peak results also showed around 30% of the respondents being stressed about two or more paid questions.

Table 10. Percentage of Transit Use of Travelers

Characteristics		**Change in Transit Use in July 2022 Compared to Pre-pandemic N (%)**			**Pearson Chi-Square (alpha)**
		Less	**More**	**Same**	
Gender	**Female**	58 (48.7)	38 (31.9)	23 (19.3)	0.4
	Male	34 (42)	25 (30.9)	22 (27.2)	
Age* **	**18~24**	49 (35.8)	53 (38.7)	35 (25.5)	<0.001
	25 and above	43 (68.3)	10 (15.9)	10 (15.9)	
Income	**Less than $15,000**	23 (39.7)	19 (32.8)	16 (27.6)	0.31
	$15,000 ~ $24,999	18 (78.3)	5 (21.7)	0 (0.0)	
	$25,000 ~ $34,999	14 (63.6)	4 (18.2)	4 (18.2)	
	$35,000 ~ $49,999	9 (40.9)	9 (40.9)	4 (18.2)	
	$50,000 ~ $75,000	6 (42.9)	4 (28.6)	4 (28.6)	
	$75,000 ~ $99,999	3 (30.0)	3 (30.0)	4 (40.0)	
	$100,000 ~ $149,999	6 (30.0)	11 (55.0)	3 (15.0)	
	More than $150,000	7 (50.0)	1 (7.1)	6 (42.9)	
	Prefer not to answer	7 (41.2)	6 (35.3)	4 (23.5)	
Ethnicity	**Asian**	46 (50.5)	21 (23.1)	24 (26.4)	0.13
	Black or African American	5 (55.6)	2 (22.2)	2 (22.2)	
	Hispanic	11 (45.8)	6 (25)	7 (29.2)	

Characteristics		Change in Transit Use in July 2022 Compared to Pre-pandemic N (%)			Pearson Chi-Square (alpha)
		Less	More	Same	
	Multiracial or Biracial	2 (33.3)	4 (66.7)	0 (0)	
	White or Caucasian	28 (40.0)	30 (42.9)	12 (17.1)	
Contracted COVID-19 Rate	No	43 (48.3)	26 (29.2)	20 (22.5)	0.83
	Unsure	6 (33.3)	7 (38.9)	5 (27.8)	
	Yes	43 (46.2)	30 (32.3)	20 (21.5)	
Motor Vehicle Access*	Yes	79 (50.3)	47 (29.9)	31 (19.7)	0.05
	No	13 (30.2)	16 (37.2)	14 (32.6)	
Education***	High School	8 (50)	4 (25)	4 (25)	<0.001
	Some College	24 (31.6)	36 (47.4)	16 (21.1)	
	Associate\Vocational\Technical Degree	1 (14.3)	3 (42.9)	3 (42.9)	
	Bachelor's Degree	25 (48.1)	15 (28.8)	12 (23.1)	
	Master’s or PHD	34 (69.4)	5 (10.2)	10 (20.4)	
Work from Home before COVID*	Never	65 (43.9)	53 (35.8)	30 (20.3)	0.08
	At least a day	27 (51.9)	10 (19.2)	15 (28.8)	
Employment	Employed	23 (41.8)	21 (38.2)	11 (20.0)	0.46
	Unemployed	69 (47.6)	42 (29.0)	34 (23.4)	
Household Member (including yourself)**	1	30 (56.6)	14 (26.4)	9 (17.0)	0.003
	2	19 (63.3)	10 (33.3)	1 (3.3)	
	3	16 (53.3)	6 (20.0)	8 (26.7)	
	4	17 (26.6)	24 (37.5)	23 (35.9)	
	More than 4	10 (43.5)	9 (39.1)	4 (17.4)	
Peak	Respondents with no peak	20 (27.0)	34 (46.0)	20 (27.0)	0.40
	Respondents with at least one peak	43 (34.1)	58 (46.0)	25 (19.8)	
		Mean Score (Standard Deviation)			ANOVA Test
PSS (max value = 40)		17.9 (6.5)	18.0 (6.7)	17.4 (5.6)	0.87
FCV (max value = 35)		15.1 (5.5)	13.5 (4.8)	15.3 (5.7)	0.14

*Note: *= significant difference at a 10% level, **= significant difference at a 5 percent level, *** = significant difference at a 1 percent level.*

However, 4% of participants were stressed solely when watching both the videos without getting stressed about paid questions. This suggests that a small number of participants may have been specifically stressed due to COVID-19. When asked about the health concern if they were to experience the same environment of that crowded bus stop and bus ride as shown in the video, approximately 15% and 14% of respondents were stressed, respectively. Approximately 18% of the respondents were stressed when asked about the major obstacles for not choosing the transit more often. Overall, the GSR peak results indicated that most participants were not stressed about COVID-19; however, a few participants exhibited stress peaks to the videos and transit-related obstacles, suggesting transit travel to be stressful for a small percentage of our sample. With some participants reporting feeling stressed about health concerns if experiencing the same environment as shown in the videos and some citing fear of COVID-19 as major reason to not use transit more often, results suggest approximately 15–20% of the students will not use transit as much in the future due to COVID-19.

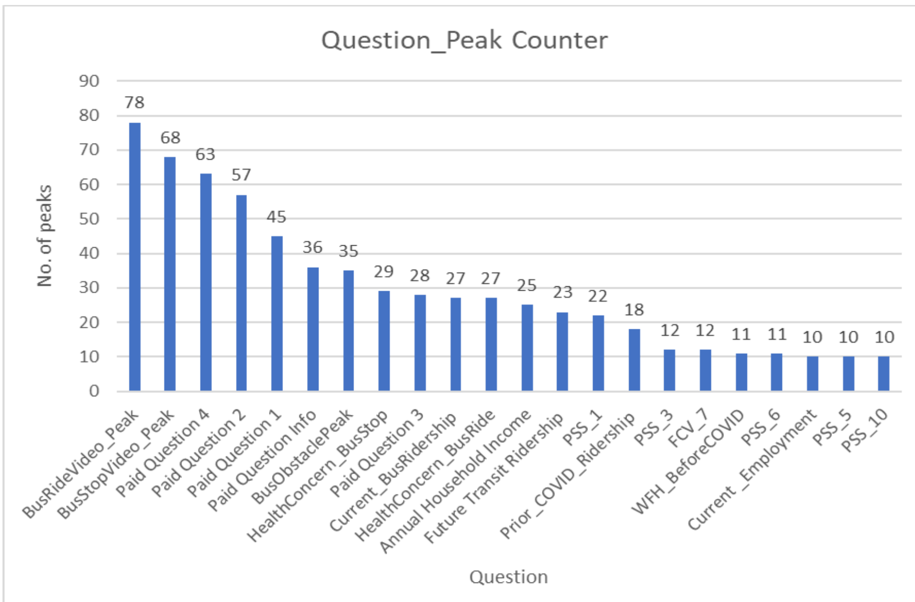


Figure 30. Number of Peaks per Question

Model of Transit Use by Students

The next step consisted of creating a response variable to identify people whose transit use increased, decreased, or remained the same from before the pandemic as compared to July 2022. The group who stated decreased transit use consisted of 46% of our sample while the group that increased their transit use was 31.5%. The remaining 22.5% indicated no change in transit use.

Discrete and categorical variables, such as age, ethnicity, etc. were converted to binary variables. Discrete variables from questions with different scales, such as importance, frequency, agreement, and likelihood were also converted to binary variables. For example, the question: "*Select all of the following reasons or obstacles that keep you from using the bus/train more often.*" asked the importance of factors (such as fear of COVID-19, vehicle ownership, etc.) that prevented them from using transit more often. If the person marked a factor as important to their decision, the variable was assigned a value of one. If not, that variable was assigned a value of 0.

Any columns (questions) with missing values due to skip logic for a particular response were dropped from the dataset. The categorical variables having more than two categories were dummy coded in the NLOGIT software. The different combinations of categorical variables were coded in the software to check the significance with the dependent variable.

As the response variable had three possible outcomes, multinomial logistic regression analysis was performed. The three outcomes considered for this study were namely: increased current ridership, decreased current ridership and the same current ridership. Equation 2 shows current ridership change function CR_{yr} to determine the probability that respondent *r* will result in current ridership change *y* (McFadden, 1981).

$$CR_{yr} = \beta_r X_{yr} + \varepsilon_{yr} \tag{2}$$

Where β_r is the coefficient of estimated parameters to be determined for current ridership change *y* (Increase, Decrease, or Same), X_{yr} is a vector of explanatory factors that influence respondent *r*'s likelihood of the ridership change result *y* and ε_{yr} represents the stochastic error term.

Marginal effects were further estimated to assess the effect of the ridership change contribution factors on the likelihood of current ridership change (Washington et al., 2020). In this study, all the explanatory variables are coded as indicator variables. The marginal effects are calculated as shown in Equation 3.

$$ME_{X_{yrk}}^{P_{yr}} = P_{yr}(X_{yrk} = 1) - P_{yr}(X_{yrk} = 0) \tag{3}$$

X_{yrk}= k^{th} indicator variable having value equals to 1 or 0, respectively; P_{yr}= probability specific to ridership change *y* for respondent; $ME_{X_{yrk}}^{P_{yr}}$ = marginal effect of the k^{th} indicator variable. The difference in probability when X_{yrk} changes from 0 to 1 while all other variables remain constant is known as marginal effect for X_{yrk}. The NLOGIT 6.0 software was employed for model estimation. Using both discrete and continuous variables, this software provides a collection of tools for creating discrete choice models (Greene, 2012).

Change in Current Transit Ridership

Tables 11 and 12 show the estimated results for the change in current transit ridership and marginal effect of variables influencing the current change outcome for each respondent, respectively. The model parameters were estimated using the maximum likelihood estimation and resulted in the McFadden Pseudo ρ^2 of 0.099. The model included three utility functions: one for increased transit ridership, one for decreased transit ridership and one for the same level of transit ridership (see Table 11 for model results).

Table 11. Current Ridership Change Model Results

Factor	*Utility Function for Change in Transit Ridership*	*Coefficient*	*Standard Error*	*z*	*Prob. | z | > z**	*95% Confidence Interval*	
Age (>24 years)	Increase	-1.04***	0.4	-2.64	0.008	-1.82	-0.27
Bus Obstacle- COVID Contraction Fear	Increase	-0.89*	0.52	-1.72	0.086	-1.91	0.13
Motor Vehicle Access	Decrease	0.99***	0.31	3.23	0.001	0.39	1.6
White	Decrease	-0.64*	0.33	-1.93	0.053	-1.3	0.01
Two or more household members	Decrease	-0.68**	0.29	-2.36	0.018	-1.25	-0.12
Unafraid of COVID (FCV Sum = 7)	Decrease	-1.20*	0.65	-1.85	0.064	-2.48	0.07
Constant	Same	-1.12***	0.32	-3.51	<0.001	-1.75	-0.5
Bus Obstacle- Active Transportation	Same	0.83**	0.36	2.33	0.019	0.13	1.53
No GSR Peak (Peak counter = 0)	Same	0.70*	0.36	1.92	0.054	-0.01	1.41
Low Stress (PSS Score between 0 and 13)	Same	-0.87*	0.49	-1.78	0.075	-1.84	0.09

Model Statistics			
Number of Observation	200	Log-likelihood at convergence	-190.35
Log-likelihood at constants	-211.34	McFadden Pseudo ρ^2	0.099

*Note: *= significant difference at a 10% level **= significant difference at a 5 percent level. *** = significant difference at a 1 percent level.*

Table 12. Marginal Effects for Current Ridership Change

Factor	Marginal Effects (Current Change in Ridership)		
	Increase	Decrease	Same
Age (>24 years)	-0.2	0.13	0.07
Bus Obstacle-COVID Contraction Fear	-0.17	0.11	0.06
Motor Vehicle Access	-0.12	0.22	-0.1
White	0.08	-0.14	0.06
Two or more household members	0.09	-0.15	0.07
Unafraid of COVID (FCV Sum = 7)	0.15	-0.27	0.12
Bus Obstacle- Active Transportation	-0.05	-0.08	0.13
No GSR Peak (Peak counter equals 0)	-0.05	-0.07	0.11
Low Stress (PSS Score between 0 and 13)	0.06	0.08	-0.14

Discussion

Several variables were found to be significant in influencing the current transit ridership change of the respondents (see Table 11). The marginal effect results shown in Table 12 depict that respondents aged above 24 years were 20% less likely to increase their current ridership. Compared to ridership remaining the same, these respondents were more likely to decrease it. A possible explanation for this could be income and occupation. The older students have a higher probability of having a stable income and work from home option which gives them more flexibility in choosing their mode of transportation. The marginal effects show that the participants who selected fear of contracting the virus as one of their reasons not to use transit more often, were 17% less likely to increase their current ridership. These participants were more likely to decrease their current ridership compared to keeping it the same. The respondents owning a motor vehicle or having access to one were 22% (0.22) more likely to decrease their current transit ridership compared to pre-pandemic ridership. These findings might be explained by factors like the comfort, convenience, and door-to-door service provided by motor vehicles. White respondents were 14% less likely to decrease their current transit usage. A possible reason for this could be explained by results from a research study that shows white respondents perceive public transportation to be safer and comfortable when compared to other ethnicities (Owen Chiu and Matthew Palm, 2022). Another possible justification could be the likelihood of white respondents living on campus or near campus (Kyle McCracken and Kelly Cox, 2018) which makes it comfortable for them to use the transit.

Respondents having two or more household members including themselves were 15% less likely to decrease their current transit ridership. However, the reason for this is not clear, but it could be possible that having multiple household members may result in limited access to a car. Individuals who obtained the lowest score (i.e., 7) on the FCV-19 Score, indicating that they were not fearful of COVID-19, had 27% less probability of decreasing their current ridership. Respondents who selected using active transportation modes like biking or walking were 13% more likely to continue their transit ridership same as pre-pandemic. As their major commute is via other modes their transit usage change is more likely to remain the same. The respondents who had no GSR peak were 11% more likely to unalter their current ridership. These groups of respondents were less likely to both decrease and increase their ridership. However, their likeness to decrease was less compared to likeness to increase. The participants with a total perceived stress score between 0 and 13 were categorized as a low stress group, indicating calmer and a relatively less stressful group. The results indicate that the respondents in this group were more likely to decrease their current transit use by 8%. Discomfort from crowding has been associated with commuting stress in public transit (Lundberg, 1976; Kozlowsky et al., 1995). These low stress respondents are more likely to decrease their current ridership due to crowded buses during the semester.

Change in Future Ridership

Like the change in current ridership, a response variable identifying the change in future transit ridership as compared to pre-pandemic ridership was created. The respondents who stated increased future transit use consisted of 25.5% of our sample while the group that stated decreased future transit use were 22.5% of the total sample. The majority (52%) of total respondents stated their future transit use will remain the same. Tables 13 and 14 show the estimated results for the change in future transit ridership logit model and marginal effect of variables influencing the change in future ridership for each respondent, respectively. The model parameters were estimated using the maximum likelihood estimation and resulted in the McFadden Pseudo of 0.074. The utility function of increased future transit ridership is shown in Table 13.

Table 13. Future Ridership Change Model Results

Factor	***Utility Function for change in Transit Ridership***	***Coefficient***	***Standard Error***	***z***	***Prob. | z | > z****	***95% Confidence Interval***	
Age (>24 years)	Increase	0.90**	0.37	2.44	0.01	0.18	1.62
Bus Obstacle Peak	Increase	-1.11*	0.58	-1.91	0.055	-2.25	0.03
No Motor Vehicle Access	Decrease	-0.70*	0.37	-1.92	0.054	-1.42	0.01
High Income	Increase	-1.64**	0.77	-2.13	0.033	-3.15	-0.13
Bus Obstacle Long Waiting Time	Increase	-0.67*	0.37	-1.78	0.075	-1.4	0.07
Constant	Increase	-0.57**	0.29	-1.97	0.049	-1.14	0
Low Stress (PSS Score between	Same	-1.03***	0.22	-4.94	0.00	-1.43	-0.62
Model Statistics							
Number of Observations	200						
Log-likelihood at constants	-204.82						
Log-likelihood at convergence	-189.76						
	0.074						

= significant difference at a 10% level **= significant difference at a 5 percent level. * = significant difference at a 1 percent level.*

Table 14. Marginal Effects of the Future Ridership Change Model

Factor	Marginal Effects (Future Change in Ridership)		
	Increase	Decrease	Same
Age (>24 years)	0.14	-0.1	-0.04
Bus Obstacle Peak	-0.17	0.11	0.06
No Motor Vehicle Access	-0.04	-0.09	0.13
High Income	-0.26	0.17	0.08
Bus Obstacle Long Waiting Time	-0.1	0.07	0.03
Low Stress (PSS Score between 0 and 13)	0.05	0.13	-0.18

Discussion

Several variables were found to be significant in influencing the change in future transit ridership of the respondents. The marginal effect results shown in Table 14 depict that respondents aged above 24 years were 14% more likely to increase their future ridership. The marginal effects show that the participants who got stressed (had a GSR peak) while answering the reasons that prevent them from using the bus more often were 17% less likely to increase their future ridership and these respondents were more likely to decrease their future ridership than to remain the same. Respondents who stated not owning a car or not having access to a motor vehicle were more likely to keep their transit ridership the same as pre-pandemic. These captive riders were less likely to decrease their future transit ridership compared to increasing their ridership. Respondents who stated having household income greater than $100,000 were 17% more likely to decrease their future transit ridership. The possible reason could be higher probability of owning a private vehicle making public transit a less viable option for these groups of respondents. Respondents who selected long waiting time as one of the obstacles for not using transit more often were 10% less likely to increase their future ridership and 7% more likely to decrease their future ridership. The results indicated that the respondents with low stress scores were more likely to decrease their future transit use by a probability of 13%.

Virtual Reality Experiment with GSR Measurements

The UPRM research team developed a Virtual Reality (VR) experiment of a typical transit scene in a city environment in which a subject had to stand and wait at a stop for the arrival of a bus, enter the bus, travel on the bus for a distance, and get out of the bus at the final stop. The objective of the VR experiment was to measure the stress level of the subject when immersed in the simulated scene using a transit service. The hypothesis was that subjects with a higher “fear” of contracting COVID-19 will exhibit higher stress levels when exposed to the conditions of a typical transit scene than those subjects that state to not have “fear” of contracting the disease.

The UPRM research team used the HTC Vive Eye Pro VR system for the execution of the experimental procedure. The equipment setup included a laptop computer, two detection sensors, one handle, and the headset with detachable headphones that reproduce sounds inside the simulation. The VR Vive Eye

Pro VR headset, shown in Figure 31, has a wireless mountable antenna to communicate with the computer that improves the subject's range of head motion and reduces safety concerns when immersed in the VR environment. Table 15 shows the general specifications of the HTC VIVE EYE PRO VR system.

Figure 31. HTC VIVE EYE PRO VR Headset

Table 15. HTC VIVE EYE PRO VR Equipment Specifications

Component	Description
Screen	Dual OLED 3.5-in diagonal
Resolution	1440 x 1600 pixels per eye (2160 x 1200 pixels combined)
Refresh rate	90 Hz
Field of view	110 degrees
Audio	Hi-Res-certified headset, Hi-Res-certified headphones (removable), high-impedance headphone support, and enhanced headphone ergonomics
Safety features	Chaperone play area boundaries and front-facing camera
Sensors	SteamVR Tracking, G-sensor, gyroscope, proximity, eye comfort setting (IPD) and eye-tracking
Connections	USB-C 3.0, DP-1.2, Bluetooth
Eye Relief	Lens distance adjustment
Controllers	SteamVR Tracking 2.0, Multifunction trackpad, Grip buttons, dual-stage trigger, System button, Menu button, and Micro-USB charging port
Room-scale	Up to 32.8 ft x 32.8 ft using four SteamVR Base Station 2.0
Base stations	Four (360-degree play area tracking coverage)

The stress level of the subjects in the experiment was measured using the NeuLog NUL-217 Galvanic Skin Response (GSR) sensor that measures the conductivity of the skin. The sensor has two GSR probes attached by means of durable rubber-coated wires and two white Velcro finger connectors, as shown in Figure 32. The sensor records the changes in the conductivity of the skin of the subjects according to the unconscious emotion effects that resulted from the sounds and scenes observed through the VR experiment. The NUL-217 has two ranges: conductivity in micro siemens and arbitrary numbers. Table 16 shows the general specifications of the NeuLog NUL-217 sensor.

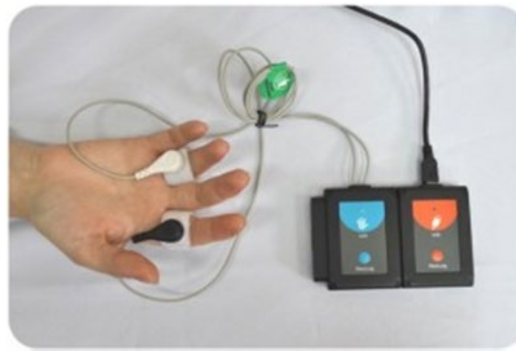


Figure 32. Neulog GSR Sensor (Source: https://neulog.com/gsr/)

The GSR equipment setup included a second laptop computer to run the NeuLog software that records the sensor measurements and the NeuLog unit with the two finger sensors. The experiment was conducted in an empty classroom or laboratory with the subject seated in an office seat and with the hand connected to the GSR unit to two fingers comfortably resting over a desk. The hand was placed over the desk to avoid sudden movements of the connected hand that could affect GSR readings. The subject held the VR handle with the other hand. The touchpad controls of the VR handle were used by the subject to "walk" inside the VR simulation. Figure 33 shows the classroom and equipment setup used for conducting the experiment. Two research assistants conducted the experiment procedures and provided the instructions to the subjects.

Table 16. NUL-GSR Sensor Specifications

	10 µS Range	**50 µS Range**	**Arbitrary Analog Units**
Range and Operation Modes	0 to 10 µS	0 to 50 µS	0 to 65,279 arb
ADC Resolution	16 bit		
Resolution	1 nS	25 nS	1 arb
Maximum Sample Rate (S/sec)	100 S / sec		

Figure 33. Room Setup for the VR Experiment with GSR Measurements

Description of Scene

The VR scene was created with the Unity 2019.4.2f1 platform. To make the VR work it is needed to have the XR Origin library that Unity provides to set up the player rig. The base VR scene consisted of a straight street segment in an urban downtown with buildings and sidewalks on both sides of the street. The street cross-section consisted of 10-ft wide lanes and 6-ft wide sidewalks. Figure 34 shows a view of the simulated urban street from the perspective of a pedestrian, where the crosswalks and the ambient traffic can be observed. A buffer area was provided between the buildings and the sidewalks to provide better depth perception to the subjects in the VR simulation. The city environment included avatars of people walking on the sidewalks, people seated and standing at a stop waiting for a bus, and people getting inside the bus. Buildings, trees, bus shelters, trashcans, and graffiti were used as props to recreate a typical cityscape. The 3D avatar models in the VR scene were acquired from the Adobe stock library (https://stock.adobe.com/). The movements of the avatars in the scene included walking, talking, coughing, and making other gestures as needed in the scene. The avatars were modified to have them wearing face masks in the simulation. Background sounds for the city traffic, the bus idle engine, the bus accelerating and stopping, and background music were included in the scene. The sounds were acquired from a royalty-free Internet source (https://www.epidemicsound.com).

Figure 34. City Street Environment in the VR Scene

Three bus stops with shelters were added along the simulated street with similar characteristics to those used for local bus stops in the San Juan Metropolitan Area (SJMA) in Puerto Rico. An open-type shelter with a steel bench and two side displays were added to each stop. The displays on the sides of the shelter showed the maps from an actual bus route and the SJMA bus network. A Nova Bus LFS vehicle was selected for the bus vehicle in the VR simulation. The Nova Bus LFS is a 40-foot-long low-floor transit bus that has been acquired in 2014 by the Metropolitan Bus Authority (MBA) in the SJMA. The bus asset was acquired from the Unity Asset Store, and it was modified to display the color strips and the logo of the Puerto Rico Integrated Transit Authority on its sides, as actual MBA buses do. The use of these bus shelters, the SJMA bus maps, and the Nova Bus vehicle was decided so subjects in the experiment could feel familiarity with the surroundings while in the VR scene.

Experimental Design

The principal objective of the experimental design was to test independent variables that recreate typical conditions faced by a bus rider when using a transit service to induce COVID-19 related stress on the subjects. The factors that impact the risk of transmission of COVID-19 are the length of exposure time, the presence of coughing or heavy breathing, the use of respirators or high-quality masks, the presence of infected persons with symptoms, the ventilation and filtration quality of the space occupied, and the distance to infected persons (CDC, 2022). Two of these risk exposure factors were included in the VR experiment as independent variables to present different potential exposure levels to the disease. The distance to potentially infected persons was represented by the quantity of riders at the bus stop (outdoor location) and inside the bus (indoor location) with two levels: LOW and HIGH OCCUPANCY. The presence of coughing was the second variable used in the experiment with two levels: COUGHING and NO COUGHING. The “coughing” sound in the VR scene was a key element in the experiment, if a subject can relate the coughing to a potentially infected person, then inducing an unconscious emotion effect that corresponds to the exposure risk of getting COVID-19 that can be measured with the GSR. Four treatment/scenarios were then created as:

1. Low occupancy with no coughing: three people waiting at the bus stop and nineteen people are seated inside the bus when the vehicle reaches the first stop. Half of the avatars in the scene are wearing a face mask. When the bus reaches the second stop, six additional people enter the vehicle. No coughing sound is included in the scenario.
2. Low occupancy with coughing: same occupancy level at the stop and inside the bus as Scenario 1, but now the coughing sound is added. Two avatars at the bus stop and inside the bus are coughing (the avatar performs the gesture of putting a hand over the mouth when coughing).
3. High occupancy with no coughing: ten people waiting at the bus stop and the bus reaches the first stop with 32 people inside. Half of the avatars in the scene are wearing a face mask. No coughing sound is included in the scenario.
4. High occupancy with coughing: same occupancy level at the stop and inside the bus as Scenario 3, but now the coughing sound is present. As in Scenario 2, two avatars at the bus stop and inside the bus are coughing (the avatar performs the gesture of putting a hand over the mouth when coughing).

Figures 35 and 36 show views of the bus stop and inside the bus at the first stop for the LOW and HIGH occupancy scenarios, respectively. The scenarios with the coughing sound (Scenarios 2 and 4) were programmed to have two different avatars coughing. Each avatar had a different sound tone when coughing and had a different frequency (one coughs every 20 seconds, and the other person coughs every 30 seconds). The two avatars seated inside the bus were in the front and the back sections of the bus.

Figure 35. Views of the Stop and Inside the Bus for the Low Occupancy Scenario

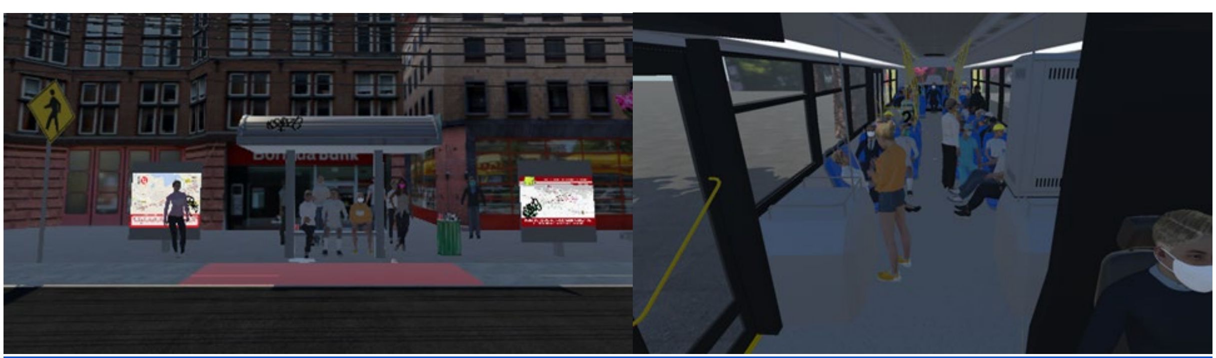


Figure 36. Views of the Stop and Inside the Bus for the High Occupancy Scenario

Experiment Procedure

The experiment procedure followed by the UPRM team consisted of ten major activities, as shown in Figure 37. The UPRM IRB approved the experimental procedures. Voluntary subjects with no compensation were recruited from June to September 2022 at two locations: the University of Puerto Rico at Mayagüez Campus and Las Catalinas Mall in the Municipality of Caguas. Each subject read and signed the informed consent to participate in the study. The informed consent ensures that the study subjects are aware of the important facts of the research, including duration, purpose, and potential benefits and risks.

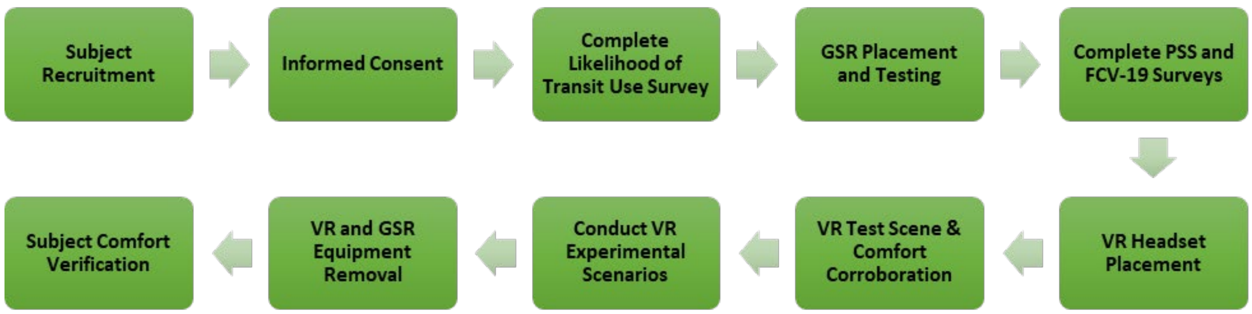


Figure 37. VR Experiment Procedure

The likelihood of transit use survey was administered to each subject before setting up the GSR sensor. Once the survey questions were completed, the GSR was placed on the fingers of the non-dominant hand of the subject and a verification of GSR measurement was made. The next step required the subject to answer the PSS and FCV-19 questionnaires. GSR measurements were taken during this process to record the initial stress level of the subject. Once fulfilling the questionnaires, the VR headset was placed on the subject. During this step, the city street scene was shown with no active animations or avatars to allow the subject to become familiar with the VR technology and learn how to use the controller to move inside the simulation.

At the start of the experiment, the subject entered the city scene next to the bus shelter. The simulation was programmed to start with the subject in front of a building behind the shelter. The instructions about the tasks the subject needed to perform throughout the simulation were virtually displayed in the headset. The first instruction provided to the subject at the start of the simulation was to walk toward the red box located in front of the shelter and wait for the arrival of the bus. Once the bus makes a complete stop next to the shelter and the bus driver activates the ramp, the subject receives the second instruction to enter the vehicle. Once the subject goes through the ramp to enter the bus and stands next to the driver, the third instruction was displayed requiring the subject to select one of three available seats inside the bus. The empty seats were located at the front, middle, and back sections of the bus. The empty seats were identified with floating numbers 1, 2, and 3. Once the subject selects the seat, the driver closes the ramp and the bus door to start the trip. The bus will reach a second stop to allow additional avatars to enter the bus. The subject was not required to perform any action or task at this stop, so no instruction was provided. Once the bus reached and stopped at the third shelter, the subject received the fourth and final instruction to exit the bus and move toward the sidewalk. The bus opened the front and back doors so the subject could decide to use either one to exit the bus.

The script created for the experiment was built in C# and includes three systems: *the Bus Waypoint System*, *the Pedestrian Sitting/Standing Waypoint System*, and *the Pedestrian Waypoint System*. The *Pedestrian Waypoint System* was used to direct the avatar around the structure to imitate spectator movement and create the impression of a busy city. A path was created for the bus to stop at each shelter and wait for the subject (waiting on the first stop) and the avatars to board using the *Bus Waypoint System*. Avatars waiting at the second bus stop use the *Pedestrian Sitting/Standing Waypoint System* to wait for the bus to stop and extend the ramp so they may board the vehicle and sit or stand inside the bus. The system randomly changes the gender of the bus driver, the color of the bus stop and the bus stripe color at each runtime.

The goal of the application was to create a virtual world where the user may walk around, wait at a bus stop, board the bus, and decide where to sit inside the bus, travel on the bus, and wait to reach the final bus stop, simulating the transportation system as closely as possible. The HTC VIVE VR headset must be connected to the computer running the latest version of the VIVE Port software for the program to function. The virtual Room is set up using the Steam services, with the required Steam VR.

The subject navigates the simulation by wearing the HTC VIVE headset and using one controller handle. The subject used the touchpad in the controller to move inside the VR simulation. The direction of the subject sightline inside the simulation was established by moving the finger in the touchpad to the direction wanted. The touchpad is then pressed or swiped forward to move the subject in the VR simulation in the direction of the head forward direction. For example, when the person looks to the right the forward direction will be through the right direction changing the other axis; meaning that if you press back it will move to the back of the head direction that is in this case left to make it the most natural way to walk. No other button in the controller was activated for the VR simulation. The subjects were trained in the use of the controller and the movement inside the simulation before the experiment was started.

Sample Size and Observations

The sample for the VR experiment consists of 32 subjects, equally divided into males and females. Each subject was assigned to one of the four treatments. Thus, four groups of eight subjects were assembled, composed of four males and four females each. Subjects did not receive monetary compensation for their voluntary participation. All the participants had to read and agree with the informed consent of the study before starting the experiment. Table 17 shows a general description of the sample composition.

The sample is predominantly composed of subjects in the age range of 18 to 34 years old (96.9% of subjects), with 75% of them UPRM students. As expected, due to the experiment being conducted in Puerto Rico, 90.6% of the sample stated to belong to the Hispanics ethnicity. In terms of income, most of the participants (62.5%) stated to have incomes less than $34,999. Some of the subjects might be reporting household income instead of personal income. Half of the participants stated that they have contracted COVID-19. Although it was not asked in the survey if the person developed symptoms or not, at least it can be assumed those subjects became aware of the risks and consequences of the disease. Another relevant characteristic of the sample is the high access of the subjects to a motor vehicle. As stated in Chapter 4, auto ownership in Puerto Rico is considerably high. Therefore, the use of transit for the study participants is expected to be reduced even before the pandemic, consistent with the behavior of the population in the U.S. territory.

Table 17. Sample Characteristics for VR Experiment

Characteristics		N	Percent
Age Group	18 to 24	28	87.5
	25 to 34	3	9.4
	35 or more	1	3.1
Ethnicity / Race	Hispanic	29	90.6
	White or Caucasian	2	6.2
	American Indian / Alaskan Native	1	3.1
Education Level Achieved	Some / High School	9	28.1
	Some College	15	46.9
	Assoc. \ Vocational \ Technical	1	3.1
	Bachelors	6	18.8
	Masters / PhD	1	3.1
Job Status	Full-Time Employee	2	6.2
	Part-Time Employee	5	15.6
	Student	24	75.0
	Unemployed	1	3.1
Has contracted COVID-19	No	15	46.9
	Unsure	1	3.1
	Yes	16	50.0
Income	Less than $15,000	10	31.2
	$15,000 to $24,999	3	9.4
	$25,000 to $34,999	7	21.9
	$35,000 to $49,999	3	9.4
	$50,000 to $75,000	3	9.4
	$75,000 to $99,999	1	3.1
	Prefer not to answer	5	15.6
Do you own or have access to a motor vehicle?	Yes	28	87.5
	No	4	12.5

Table 18 presents the survey responses to the use of transit and the two psychometric tests used PSS and FCV-19. The survey responses confirm the sample is composed primarily of people that use private motor vehicles for their daily mobility. Although 28.1% of the sample stated to use transit before the pandemic, their frequency of use is very limited. Only two subjects (6.2%) were considered frequent users previous to COVID-19, based on the definition used in this study. The negative impact to the frequency of use of transit during COVID-19 follows the established trend in the literature reviewed and the analysis of transit ridership conducted in this study. The number of frequent transit users during COVID-19 in the sample is reduced in half, to just one subject. On the other hand, there are 25 subjects who stated that they never used transit during COVID-19. The challenge to increase transit ridership in Puerto Rico after the pandemic is significant and will require major efforts to convince the population to use transit. Only four subjects (12.5%) stated to be interested in increasing the use of transit once the effects of COVID-19 are gone. Most of the subjects (61.5%) stated to keep at the same level of use of transit they had before COVID-19 once the pandemic ends. One of the frequent transit users before COVID-19 stated to be willing to use transit less in the future after COVID-19.

Table 18. Stated Use of Transit and Stress Test Results

Characteristics			N	Percent
How often did you ride the bus/train (Pre–COVID-19)?	Never		23	71.5
	Less than 1 trip a month		6	18.8
	1 to 4 trips a month		1	3.1
	1 to 5 trips a week		1	3.1
	6 to 10 trips a week		0	0.0
	More than 10 trips a week		1	3.1
How often do you currently ride the bus/train? (During COVID-19)	Never		25	78.1
	Less than 1 trip a month		4	12.5
	1 to 4 trips a month		2	6.2
	1 to 5 trips a week		0	0.0
	6 to 10 trips a week		0	0.0
	More than 10 trips a week		1	3.1
After COVID-19, will you ride transit more, less, or the same amount as before COVID-19?	Less / Much Less		7	21.9
	Same as Before		21	65.6
	More / Much More		4	12.5
Stress Test	**Average**	**Std. Deviation**	**Minimum**	**Maximum**
PSS	23.2	3.7	16	30
FCV-19	16.4	5.8	8	31

Table 18 also shows the results from the psychometric tests PSS and FCV-19 that measure the level of stress and fear of COVID-19, respectively, in the sample. Figure 38 shows the histograms for both scores obtained from the sample. The average PSS score in the sample was 23.2 points. As the PSS gets higher the greater is the perceived stress of a person. Cohen et al. (1983) did not suggest cut-off scores to establish an interpretation of the severity of the stress in the person. Nevertheless, users of the PSS tool have suggested cutoff points for determining the stress level of a person. For example, the Department of Administrative Services of the State of New Hampshire suggests a category of low stress level for PSS from 0 to 13 points, a moderate stress level for scores between 14 and 26 points, and a high perceived stress for scores between 27 and 40 points (NH-DAS, 2023). Using the NH scale, the sample could be identified as 0% in low stress, 78.1% in moderate stress, and 21.9% in high perceived stress.

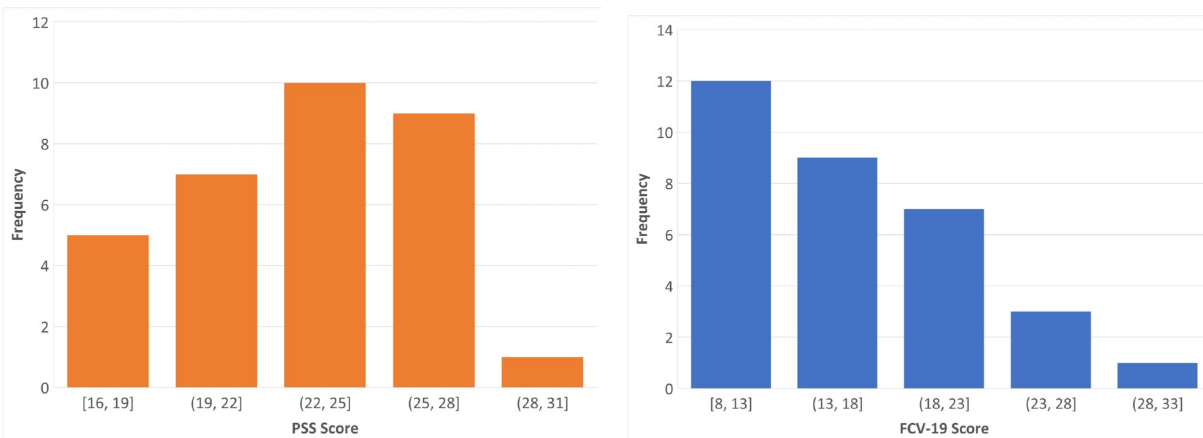


Figure 38. Histograms of Psychometric Tests PSS and FCV-19S

On the other hand, FCV-19 scores obtained for the sample show a skew toward lower scores (the FCV-19 has a range between 7 and 35 points. The average FCV-19 is 16.4 points, with only 28.1% of the sample having an FCV-19 over 21 points (midpoint of the FCV-19 range). As the score of the FCV-19 goes higher, the greater the perceived fear of COVID-19 of a person.

GSR Data and Modeling Results

The VR experiment along with the use of GSR measurements looked to identify if stress level or the perceived fear of COVID-19 affected the decision of persons to use transit. Thirty-two subjects were immersed in a simulated transit scene in a city using VR technology. The experiment required subjects to share space with avatars representing other transit users. The treatments included two levels of occupancy at the bus stop and inside the bus, and the presence or absence of "potentially infected" avatars coughing in the scene. The four treatments were used to assess if these factors provoked stress levels that could be measured using the GSR sensor. The research team recorded the skin conductivity responses (SCR) from the subjects and measured the peaks that were registered by the equipment. Table 19 shows the experiment results for four original treatments in the experiment. The response measurements for the four combinations of scenarios were also included. Two counts of peaks from the GSR data were used: the total number of peaks recorded in the entire VR simulation (SCR) and the number of peaks recorded in specific moments in the scene that were related to COVID-19 (CR-SCR).

Table 19. Skin Conductivity Response from VR Experiment Scenarios

Factors	SCR	CR-SCR
Low Occupancy / No Cough (Scenario 1)	7.6	0.8
Low Occupancy + Cough (Scenario 2)	12.1	3.2
High Occupancy / No Cough (Scenario 3)	9.1	1.1
High Occupancy + Cough (Scenario 4)	4.6	3.0
Low Occupancy (Scenarios 1+2)	9.9	2.0
High Occupancy (Scenarios 3+4)	6.9	2.1
Presence of Cough (Scenarios 2+4)	8.4	3.1
No Cough (Scenarios 1+3)	8.4	0.9

The dataset consisted of 32 observations, equally divided in the four experimental treatments. Selected responses from the survey were coded as binary variables to represent subject characteristics or perceptions that could explain the variability in the GSR measurements. The *GENDER* variable was assigned a value of zero (0) for a male subject and one (1) for a female subject. The *NO-VEHICLE* variable was defined for the question about the availability of a private motor vehicle for transportation, assigning a value of zero (0) to subjects that stated to have access to or owning a private motor vehicle and a value of one (1) otherwise. The *COVID* variable was assigned a value of one (1) for subjects that were infected with *COVID* and a value of zero (0) otherwise.

The responses from the stated use of transit before and during the pandemic, and the future use of transit once the COVID-19 pandemic has terminated were also coded as binary variables. The *BEFORE COVID* variable was assigned a value of one (1) to those subjects who stated having used transit before the COVID-19 pandemic (regardless of their frequency of use) and a value of zero (0) otherwise. The *DURING COVID* variable was assigned a value of zero (0) for non-transit users during the pandemic and a value of one (1) for those subjects who stated using transit during the COVID-19 pandemic (regardless of their frequency of use). The *FUTURE TRANSIT USE* variable took a value of zero (0) for subjects who stated they will use less transit in the future once COVID-19 is gone and a value of one (1) for those subjects who stated to use the same or more transit in the future.

The Kruskal-Wallis test was performed on the SCR and CR-SCR response variables to identify significant correlations with the independent variables. A Poisson regression model was calibrated on the SCR and CR-SCE response variables to describe the combined effects of the independent variables.

The Kruskal-Wallis test is a non-parametric approach to the one-way ANOVA to determine if there were significant differences between the median values of the distributions of the SCR and CR-SCR based on the levels of the independent variables. Table 20 shows the results for the Kruskal-Wallis test based on five independent variables. The h-value is the test statistic, which is used to calculate the p-value of the parameter.

The Kruskal-Wallis test results show that the *NO-VEHICLE* and *HIGH OCC + COUGH* variables have a significant effect on the median values of the SCR measurement with p-values lower than 0.10. The

HIGH OCC + COUGH variable represents the treatment with the high occupancy of transit riders at the bus stop and inside the bus, and it included the effect from the avatars coughing on the simulation. The combined effects of having a large group of persons waiting for the bus and a large group of riders inside the bus, in addition to the presence of coughing, affected the stress level of the subjects in the experiment. The only subject characteristic that influenced the stress level of the subject was the stated accessibility to a motor vehicle. Subjects without access to a motor vehicle are usually transit captive riders. The daily dependance on transit during the pandemic could be associated with the perceived stress when observing the VR scenarios in the experiment. For the case of the CR-SCR response variable, the PSS resulted in having a significant effect on the median value. No other subject characteristic resulted in a significant effect on the median value of the CR-SCR response. The test also confirms that the experimental treatments in the VR simulation have a significant effect on the CR-SCR measurements.

Table 20. Kruskal-Wallis Test Results on the Skin Conductivity Responses

	SCR		CR-SCR	
Parameter	**h-value**	**p-value**	**h-value**	**p-value**
GENDER	0.013	0.910	0.002	0.968
NO-VEHICLE	**4.016**	**0.045***	1.058	0.304
COVID	0.224	0.636	0.048	0.826
BEFORE COVID	0.543	0.461	0.240	0.624
DURING COVID	0.231	0.631	0.937	0.333
FUTURE TRANSIT USE	0.042	0.837	0.891	0.345
PSS	7.714	0.807	**20.928**	**0.051***
FCV-19	15.303	0.430	20.137	0.167
HIGH OCC	0.349	0.555	**3.331**	**0.068***
LOW OCC + COUGH	1.838	0.175	**6.226**	**0.013***
HIGH OCC + COUGH	**4.135**	**0.042***	**3.502**	**0.061***
COUGH	0.345	0.557	**14.299**	**<0.001***

*Note: * = the parameter has a significant effect on the response variable at a 90% confidence level.*

A Poisson regression model was developed to explain the effects on the CR-SCR response based on subject and scenario characteristics. Table 21 shows the parameter coefficients with their p-values in parentheses. A p-value of 0.10 was used as threshold to establish statistical significance.

The results from the Poisson regression establish that the two experiment treatments related to the presence of coughing in the simulation scenarios, regardless of the level of occupation, increased the CR-SCR measurements in the subjects. The regression model explains about 52% of the variability in the data, which can be considered more than adequate for GSR measurements.

Table 21. Results for the Poisson Regression Model Calibration

Parameter	**Coefficient**	**Std. Error**	**z**	**p-value**
INTERCEPT	0.2643	1.066	0.248	0.804
HIGH OCC	0.5115	0.598	0.856	0.392
LOW OCC + COUGH	**1.8078**	**0.563**	**3.210**	**0.001***
HIGH OCC + COUGH	**1.4332**	**0.487**	**2.941**	**0.003***
BEFORE-COVID	0.3908	0.454	0.861	0.389
DURING-COVID	0.1572	0.514	0.306	0.759
FUTURE TRANSIT USE	-0.1246	0.423	-0.295	0.768
COVID	0.2847	0.353	0.806	0.420
PSS	-0.0419	0.046	-0.920	0.358
FCV19	0.0044	0.024	0.188	0.851
Log-likelihood	-46.955	**Pearson Chi^2**		19.4
Deviance	22.420	**Pseudo R^2**		0.5297

This result supports the proposition made for the VR simulation study that coughing, one of the relevant exposure factors of COVID-19, provokes a reaction in the subjects by increasing their stress level. Subjects that observed the scenario *LOW OCCUPANCY + COUGHING* had 6.1 times more peaks in the CR-SCR measures than those in the *LOW OCCUPANCY* scenario. Subjects that observed the scenario *HIGH OCCUPANCY + COUGHING* had 4.2 times more peaks in the CR-SCR measures. The intensity and the sound used for the coughing effect in the simulation of the two treatments was the same.

None of the variables of the subject characteristics or the stated use of transit were found to be statistically significant in the regression model. Although the coughing effect was found to increase the skin conductivity response (i.e., provoke higher stress levels on the subjects), the direct effect or its connection with the actual transit use is not straightforward. The sample of subjects in this experiment is composed predominantly of young people who were not frequent transit users. A future experimental trial could focus on identifying frequent transit users from different age groups that can be used to study their stress levels and the change in transit use.

Chapter 7. Conclusions

Study Overview

The disruption caused by COVID-19 pandemic prompted many people to reevaluate their daily routines and travel patterns. The effect of preventive measures such as stay-at-home orders, mandatory face coverings, and social distancing was prominent in the transportation sector where travel decreased significantly for all modes. With highway travel and toll roads rebounding quickly, the much slower rebound of transit ridership raises a concern that transit users might not fully return in the short or medium term. Despite efforts by transit agencies to ramp up the operations, the transit sector has struggled to regain pre-pandemic level ridership. One reason may be an individual's psychological factors like stress/fear of catching the virus in mass transportation systems like transit. These factors could play a major role in predicting the future use of transit. As the pandemic continues to evolve, predicting the change in post-pandemic travel behavior remains a question.

This research's framework is designed to shed light on the future of transit ridership. The study included data collection in three experiment phases. In the first phase, the results from a survey of travelers' stated use of transit before, during, and after the pandemic, were examined. The survey focused on identifying factors associated with the change in transit use, including stress and fear of COVID-19. In the second phase, the traveler's stress levels during the survey were measured using Galvanic Skin Response (GSR) and facial expression, along with self-reported responses to the survey. This provided additional insight into the reasons why many travelers have not returned to transit. The design of the third phase utilized an immersive virtual reality (VR) environment to simulate the transit experience in the near future. This aimed to provide a deeper knowledge into how people perceive fear/stress of COVID-19 in context of future transit travel. Thus, the purpose of the research was to assist public and private transit agencies make a better-informed choice of strategy, focusing on measures directed to regain confidence in transit riders.

Study Conclusions

The results from the survey of travelers found that approximately 41% of respondents reduced their use of transit after the pandemic declaration in March 2020 and 45.5% stated they were less willing to use transit in the future even after the pandemic is over. Respondents who stated a lower use of transit during the pandemic also had higher average stress levels and higher fear of COVID-19. A Random Forest Classification Model and a SHAP Value Plot were used to identify factors relevant to the stated reduced transit use for those travelers that were frequent transit users before the pandemic. Household size and annual income, the comfort level of a person when faced with a crowded bus, the fear or risk of contracting COVID-19, along with age and gender characteristics, were among the key factors associated with the stated reduction in transit use.

In the second phase of the study, a nearly identical survey was conducted in the human behavior laboratory (HBL) at Texas A&M University where respondent stress levels were measured while taking the survey. The findings from the second phase revealed that almost half of the respondents, 46%, decreased their use of public transportation after the pandemic was declared in March 2020 and nearly a quarter, 22.5%, stated they would use transit less even after the pandemic ends. This is less than in the larger survey of the general population and is likely due to the participants being younger (students) who, in general, have less health impacts when infected by COVID-19. Analyzing the peak stress events, it was found that both the first-perspective videos of a crowded bus stop and a crowded bus ride caused stress in a majority of participants. However, participants were also stressed about questions that would increase their payment for taking the survey and those questions were linked to the videos. Respondents who did not show any stress were more likely to not change their transit use. Also, participants who indicated stress while answering the question regarding the reasons that prevented them from using the bus often were 11% more likely to decrease their future transit ridership.

The third phase of the study consisted of a VR experiment conducted at the University of Puerto Rico at Mayagüez that included the use of skin conductivity response measurements and the stated use of transit questionnaire. The VR simulation was an effective tool to immerse subjects in a typical transit scene and to record peaks in their stress levels based on two sizes of crowding and the presence of coughing, two of the main COVID-19 exposure factors identified from the literature. The results from a non-parametric test identified significant effects on the skin conductivity response measures from COVID-19 related events in the simulation from the PSS scores and the simulation treatment levels. The effects from seeing large groups of persons gathering at a stop waiting for a bus and having to share the confined space inside the bus with a large group of transit riders, in addition to the presence of coughing, was found to be significant on the stress level of the subjects. A Poisson regression confirmed the increasing effect on the stress level of subjects when they observed and heard nearby avatars coughing at the stop and inside the bus. The significant effect that coughing has on reducing the willingness to use transit during the pandemic can be established from the study results. Nevertheless, the effects of subject characteristics and the possible use of transit in the future once COVID-19 is gone cannot be established directly from the results of the VR experiment as the sample cannot be representative of frequent transit users in Puerto Rico. The sample was biased toward young people with ample availability of private automobiles to meet their transportation needs. This trend in the sample is consistent with the Puerto Rico population and the low willingness to use transit that is currently present in the U.S. territory. It is therefore recommended that a similar VR experiment be conducted with a different sample of subjects that can be representative of frequent transit users. This future effort should include conducting the VR experiment with GSR measurements at different locations and transit contexts in the U.S.

Researchers feel that the use of the FCV and PSS scales added valuable insight into respondents stated travel behavior. There were strong relationships between these scales and travel choices. The use of GSR to measure stress, particularly when watching first person videos and when participating in VR, also helped to identify travelers' feelings toward travel options. However, there were two issues that could be improved: (1) the use of the high-end, but uncommon, VR headset at Texas A&M caused programming problems and ultimately resulted in the VR experiment not happening at Texas A&M; and (2) the ability of participants to earn additional money, even just $1, appears to cause significant stress in many people and thus we would try to avoid that.

This research focuses on stress and fear of COVID-19's impact on transit use. However, it is important to note the other key factors found to limit transit use: larger household size, high annual income, preference for shorter waiting times, and working from home. The latter three are often found in the literature, we feel that the larger household size may indicate a higher likelihood of having an automobile available for use and thus less use of transit.

The research found there may be as many as 35% to 45% of respondents who will not use transit as much in the future due to COVID-19. This higher range occurs if both the responses "Extremely" and

“Very” are considered indicators of future travel decisions for survey questions asking the importance or likeliness of COVID-19 factors in determining that respondents future transit use. However, if we consider only those respondents who indicated “Extremely Important,” “Extremely Likely,” and “Extremely Uncomfortable,” then a lower range of approximately 15% to 25% of the respondents will not use transit as much in the future due to COVID-19. When examining Texas A&M students only, the percentage who may use less transit due to COVID-19 is likely smaller than 15%, but greater than 0%. So, even amongst this group, COVID-19 has a negative impact on transit use. Therefore, in addition to telecommuting and mode shifts caused by the pandemic, transit agencies must overcome the stresses and fears that the commuters continue to have related to COVID-19 for ridership to return to pre-pandemic levels.

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Appendix A. Travel Survey (English Version)

Start of Block: Information/Consent

Q1.1 **Title of Research Study: Predicting Travel and Congestion in a Post-Pandemic America**

Investigator: Dr. Mark Burris

Why am I being asked to take part in this research study?
You are invited to participate in this study because we are trying to learn more about the change in travel with the onset of COVID-19. This study will try to predict future use of transit given fear of COVID-19.

You were selected as a possible participant in this study because you can read and understand English or Spanish (survey is written in both English and Spanish) and you are at least 18 years old.

Why is this research being done?
The survey is designed to predict the change in travel due to COVID-19 among travelers using transit.

What happens if I say "Yes, I want to be in this research"?
You will be asked to fill out a 10-minute survey.

What happens if I do not want to be in this research?
Your participation in this study is voluntary. You can decide not to participate in this research and it will not be held against you. You can leave the study at any time.

Is there any way being in this study could harm me?
There are no sensitive questions in this survey that should cause discomfort. However, you can skip any question you do not wish to answer, or exit the survey at any point.

What happens to the information collected for the research?
You may view the survey host's confidentiality policy at: https://www.qualtrics.com/privacy-statement/

Your name and email address will be stored separately from your survey data, and is only being collected for the purpose of the award distribution. All identifiable information will be kept on a password protected computer and is only accessible by the research team. Compliance offices at Texas A&M may be given access to the study files upon request. Your information will be kept confidential to the extent allowed by law. The results of the research study may be published but your identity will remain confidential.

What else do I need to know?
If you agree to take part in this research study, you will be eligible to enter a random drawing for one of 10 amazon gift cards worth $100. The selected participant for the gift card would be notified through an email along with the link/code to redeem the Amazon Gift Card. The participants should expect to receive their gift card in the second week of June 2022.

Who can I talk to?
Please feel free to ask questions regarding this study. You may contact Dr. Mark Burris via email at

mburris@tamu.edu or by phone 979-845-9875 if you have additional questions or concerns. You may also contact the Human Research Protection Program at Texas A&M University (which is a group of people who review the research to protect your rights) by phone at 1-979-458-4067, toll free at 1-855-795-8636, or by email at irb@tamu.edu.

If you want a copy of this consent for your records, you can print it from the screen.
If you wish to participate, please click the **Start the Survey** below and you will be taken to the survey.
If you do not wish to participate in this study, please close the tab of your browser.

Para realizar la encuesta en español acceda al enlace: encuestadeviaje.org

End of Block: Information/Consent

Start of Block: Transit Survey

Q2.1 ***Thank you for taking time to fill the survey.***
Do you own a motor vehicle or have access to a motor vehicle (car, truck, SUV, motorcycle, etc.)?

◯ Yes

◯ No

Q2.2 **Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? *(Count each direction of travel as one trip)***

◯ More than 10 trips a week

◯ 6 to 10 trips a week

◯ 1 to 5 trips a week

◯ 1 to 4 trips a month

◯ Less than 1 trips a month

◯ Never

Q2.3 **Currently, how often do you ride the bus/train? (Count each direction of travel as one trip)**

- More than 10 trips a week
- 6 to 10 trips a week
- 1 to 5 trips a week
- 1 to 4 trips a month
- Less than 1 trip a month
- Never

Q2.4 **After COVID-19 is no longer a threat, how do you expect your use of bus/train to change relative to before the COVID-19 pandemic.**

- Much less than before
- Somewhat less than before
- About the same
- Somewhat more than before
- Much more than before

Display This Question:

If Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? (Cou... = More than 10 trips a week

Or Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? (Cou... = 6 to 10 trips a week

Or Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? (Cou... = 1 to 5 trips a week

Or Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? (Cou... = 1 to 4 trips a month

And If

Currently, how often do you ride the bus/train? (Count each direction of travel as one trip) = Less than 1 trips a month

Or Currently, how often do you ride the bus/train? (Count each direction of travel as one trip) = Never

Q2.5 **How likely are you willing to travel again by bus/train for each of the following scenarios**

	Extremely unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Extremely likely
If most of the population is vaccinated	○	○	○	○	○
Proper cleanliness and social distancing is maintained	○	○	○	○	○
Parking cost is increased	○	○	○	○	○
If the buses can reach more destinations	○	○	○	○	○
If the buses run more often	○	○	○	○	○
I must travel to the office more because I am working from home less	○	○	○	○	○

Q2.6 **Select all of the following reasons or obstacles that keep you from using bus/train more often? (Select up to maximum of three)**

- ☐ Bus service is not in my area or can't reach a desired destination
- ☐ Travel time for the bus service is too unreliable
- ☐ Need my vehicle for making trips or running errands during the day
- ☐ Fear of getting COVID
- ☐ It makes me feel unsafe to walk to or wait at a bus stop
- ☐ Long waiting time or high trip delays in the bus service
- ☐ I don't have information about the bus service / it is difficult to use the bus service
- ☐ I drive my own vehicle
- ☐ I use other modes (i.e. walking, bicycle, scooter, etc.)
- ☐ I work more often from home
- ☐ Other. Please specify: ____

Display This Question:

If Thank you for taking time to fill the survey. Do you own a motor vehicle or have access to a moto... = Yes

Q2.7 **How important are the following factors for using your personal motor vehicle for daily travel?**

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
I don't have to wait for the bus	○	○	○	○	○
Comfort of my motor vehicle	○	○	○	○	○
Shorter travel time	○	○	○	○	○
Cleanliness of the vehicle	○	○	○	○	○
Lower chances of catching COVID	○	○	○	○	○
Can run errands/shopping at any time	○	○	○	○	○
The bus/train does not go to the places I need to go	○	○	○	○	○

End of Block: Transit Survey

Start of Block: Personal Data / Demographics Survey

Q3.1
Which of the following category best describes your age?

○ 18 to 24

○ 25 to 34

○ 35 to 44

○ 45 to 54

○ 55 to 64

○ 65 and over

Q3.2 **Which of the following best describes you?**

- ◯ Asian or Pacific Islander
- ◯ Hispanic or Latino
- ◯ White or Caucasian
- ◯ Native American or Alaskan Native
- ◯ Black or African American
- ◯ Multiracial or Biracial
- ◯ A race/ethnicity not listed here. Please specify ____________________

Q3.3 **Which of the following best describes you?**

- ◯ Female
- ◯ Male
- ◯ Prefer not to say
- ◯ Other ____________________

Q3.4 **What is the highest level of education you accomplished?**

- ◯ Some High School
- ◯ High School
- ◯ Some College
- ◯ Associate \ Vocational \ Technical Degree
- ◯ Bachelor's Degree
- ◯ Masters or PHD

Q3.5 **Indicate your current employment status.**

- Employed full-time
- Employed part-time
- Student
- Retired
- Homemaker
- Unemployed

Q3.6 **How many days did you work from home in a week before March 2020 (COVID-19) ?**

- 0 days
- 1-2 days
- 3-4 days
- 5 days
- 6-7 days

Q3.7 **Have you contracted COVID-19?**

- Yes
- No
- Unsure
- Prefer not to say

Q3.8 **What is your annual household income? (Include the incomes of all household members)**

- Less than $10,000
- $10,000 - $14,999
- $15,000 - $24,999
- $25,000 - $34,999
- $35,000 - $49,999
- $50,000 - $74,999
- $75,000 - $99,999
- $100,000 - $124,999
- $125,000 - $149,999
- $150,000 - $199,999
- More than $200,000
- Prefer not to answer

Q3.9 **How many people live in your household? Include yourself.**

- 1
- 2
- 3
- 4
- More than 4

End of Block: Personal Data / Demographics Survey

Start of Block: PSS Survey

Q4.1 **In the last month, how often have you been upset because of something that happened unexpectedly?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.2 **In the last month, how often have you felt that you were unable to control the important things in your life?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.3 **In the last month, how often have you felt nervous and “stressed”?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.4 **In the last month, how often have you felt confident about your ability to handle your personal problems?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.5 **In the last month, how often have you felt that things were going your way?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.6 **In the last month, how often have you found that you could not cope with all the things that you had to do?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.7 **In the last month, how often have you been able to control irritations in your life?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.8 **In the last month, how often have you felt that you were on top of things?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.9 **In the last month, how often have you been angered because of things that were outside of your control?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.10 **In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?**

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

End of Block: PSS Survey

Start of Block: Fear of COVID-19 Survey

Q5.1
Please indicate your level of agreement or disagreement with the following statements:

I am most afraid of COVID-19.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.2 **It makes me uncomfortable thinking about COVID-19.**

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.3 **My hands become clammy when I think about COVID-19.**

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.4 **I am afraid of losing my life because of COVID-19.**

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.5 **When watching news and stories about COVID-19 on social media, I become nervous or anxious.**

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.6 **I lose sleep because I'm worried about getting COVID-19.**

- ○ Strongly disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Strongly agree

Q5.7 **My heart races or palpitates when I think about getting COVID-19.**

- ○ Strongly disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Strongly agree

End of Block: Fear of COVID-19 Survey

Start of Block: Video Quiz

Q6.1 **Click on the bus design you like the best**

○ 

○ 

○ 

Q6.2 **How comfortable are you waiting for the bus at the bus stop shown in the video?**

◯ Extremely uncomfortable

◯ Somewhat uncomfortable

◯ Neither comfortable nor uncomfortable

◯ Somewhat comfortable

◯ Extremely comfortable

Q6.3 **How comfortable are you riding in the bus shown in the video?**

◯ Extremely uncomfortable

◯ Somewhat uncomfortable

◯ Neither comfortable nor uncomfortable

◯ Somewhat comfortable

◯ Extremely comfortable

Q6.4 **If your bus was as crowded as the videos showed, would you still use the bus?**

- ◯ Yes
- ◯ No
- ◯ Maybe

Q6.5 **If you have any additional comments on travel, you are welcome to share them in the space below.**

____

End of Block: Video Quiz

Start of Block: Prize Information

Q7.1 **If you wish to enter the $100 gift card drawing, please go to the link below to provide us with your contact information. By doing this your answers will be saved separately to your personal information.**
If you do not wish to participate in the drawing, you can complete your participation in the survey by clicking on the "End the Survey" button. Thanks

Link to enter prize drawing: https://tti.qualtrics.com/jfe/form/SV_6wZumjPwAefQKEK

End of Block: Prize Information

Appendix B. Travel Survey Augmented with GSR

Start of Block: Initial info

Q1.1 Enter Subject ID

____

Q1.2 *Thank you for taking time to fill the survey.*
Title of Research Study: Predicting Travel and Congestion in a Post-Pandemic America

Why is this research being done?
You are invited to participate in this study because we are trying to learn more about the change in travel with the onset of COVID-19. This study will try to predict future use of transit given fear of COVID-19.

End of Block: Initial info

Start of Block: Transit Survey

Q2.1 *Thank you for taking the time to fill this survey.*
Do you own a motor vehicle or have access to a motor vehicle (car, truck, SUV, motorcycle, etc.)?

○ Yes

○ No

Q2.2 Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? *(Count each direction of travel as one trip)*

○ More than 10 trips a week

○ 6 to 10 trips a week

○ 1 to 5 trips a week

○ 1 to 4 trips a month

○ Less than 1 trips a month

○ Never

Q2.3 Currently, how often do you ride the bus/train? (Count each direction of travel as one trip)

- More than 10 trips a week
- 6 to 10 trips a week
- 1 to 5 trips a week
- 1 to 4 trips a month
- Less than 1 trips a month
- Never

Q2.4 After COVID-19 is no longer a threat, how do you expect your use of bus/train to change relative to before the COVID-19 pandemic.

- Much less than before
- Somewhat less than before
- About the same
- Somewhat more than before
- Much more than before

Display This Question:

If Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? (Cou... = More than 10 trips a week

Or Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? (Cou... = 6 to 10 trips a week

Or Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? (Cou... = 1 to 5 trips a week

Or Prior to the COVID-19 pandemic declared in March 2020, how often did you ride the bus/train? (Cou... = 1 to 4 trips a month

And If

Currently, how often do you ride the bus/train? (Count each direction of travel as one trip) = Less than 1 trips a month

Or Currently, how often do you ride the bus/train? (Count each direction of travel as one trip) = Never

Q2.5 How likely are you willing to travel again by bus/train for each of the following scenarios

	Extremely unlikely	Somewhat unlikely	Neither likely nor unlikely	Somewhat likely	Extremely likely
If most of the population is vaccinated	○	○	○	○	○
Proper cleanliness and social distancing is maintained	○	○	○	○	○
Parking cost is increased	○	○	○	○	○
If the buses can reach more destinations	○	○	○	○	○
If the buses run more often	○	○	○	○	○
I must travel to the office more because I am working from home less	○	○	○	○	○

Q2.6 Select all of the following reasons or obstacles that keep you from using bus/train more often? (Select up to maximum of three)

- ☐ Bus service is not in my area or can't reach a desired destination
- ☐ Travel time for the bus service is too unreliable
- ☐ Need my vehicle for making trips or running errands during the day
- ☐ Fear of getting COVID
- ☐ It makes me feel unsafe to walk to or wait at a bus stop
- ☐ Long waiting time or high trip delays in the bus service
- ☐ I don't have information about the bus service / it is difficult to use the bus service
- ☐ I drive my own vehicle
- ☐ I use other modes (i.e. walking, bicycle, scooter, etc.)
- ☐ I work more often from home
- ☐ Other. Please specify: ____

Display This Question:

If Thank you for taking the time to fill this survey. Do you own a motor vehicle or have access to... = Yes

Q2.7 How important are the following factors for using your personal motor vehicle for daily travel?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
I don't have to wait for the bus	○	○	○	○	○
Comfort of my motor vehicle	○	○	○	○	○
Shorter travel time	○	○	○	○	○
Cleanliness of the vehicle	○	○	○	○	○
Lower chances of catching COVID	○	○	○	○	○
Can run errands/shopping at any time	○	○	○	○	○
The bus/train does not go to the places I need to go	○	○	○	○	○

Display This Question:

If Currently, how often do you ride the bus/train? (Count each direction of travel as one trip) = More than 10 trips a week

Or Currently, how often do you ride the bus/train? (Count each direction of travel as one trip) = 6 to 10 trips a week

Or Currently, how often do you ride the bus/train? (Count each direction of travel as one trip) = 1 to 5 trips a week

Q2.8 How important are the following factors for you to ride the bus/train for daily travel?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Not worrying about driving	○	○	○	○	○
Environment Friendly	○	○	○	○	○
Less costly (Savings in parking, fuel, and maintenance of my vehicle)	○	○	○	○	○
Routes take me places of interest and need	○	○	○	○	○
Free parking at bus station or curbside	○	○	○	○	○
Social Interaction	○	○	○	○	○
I do not have access to a motor vehicle	○	○	○	○	○
The service schedule is reliable and has accurate departure times	○	○	○	○	○
Health or disability condition	○	○	○	○	○
Lower commuting times	○	○	○	○	○

End of Block: Transit Survey

Start of Block: Personal Data / Demographics Survey

Q3.1
Which of the following category best describes your age?

- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 to 64
- 65 and over

Q3.2 Which of the following best describes you?

- Asian or Pacific Islander
- Hispanic or Latino
- White or Caucasian
- Native American or Alaskan Native
- Black or African American
- Multiracial or Biracial
- A race/ethnicity not listed here. Please specify ____

Q3.3 Which of the following best describes you?

- Female
- Male
- Prefer not to say
- Other ____

Q3.4 What is the highest level of education you accomplished?

- Some High School
- High School
- Some College
- Associate \ Vocational \ Technical Degree
- Bachelors Degree
- Masters or PHD

Q3.5 Indicate your current employment status.

- Employed full-time
- Employed part-time
- Student
- Retired
- Homemaker
- Unemployed

Display This Question:

If Indicate your current employment status. = Employed full-time

Or Indicate your current employment status. = Employed part-time

Q3.6 How many days do you currently work from home in a week ?

- 0 days
- 1-2 days
- 3-4 days
- 5
- 6-7 days

Q3.7 How many days did you work from home in a week before March 2020 (COVID-19) ?

- 0 days
- 1-2 days
- 3-4 days
- 5 days
- 6-7 days

Q3.8 Have you contracted COVID-19?

- Yes
- No
- Unsure
- Prefer not to say

Q3.9 What is your annual household income? (Include the incomes of all household members)

- Less than $10,000
- $10,000 - $14,999
- $15,000 - $24,999
- $25,000 - $34,999
- $35,000 - $49,999
- $50,000 - $74,999
- $75,000 - $99,999
- $100,000 - $124,999
- $125,000 - $149,999
- $150,000 - $199,999
- More than $200,000
- Prefer not to answer

Q3.10 How many people live in your household? Include yourself.

- 1
- 2
- 3
- 4
- More than 4

End of Block: Personal Data / Demographics Survey

Start of Block: PSS Survey

Q4.1 Timing
Page Submit
Click Count

Q4.2 In the last month, how often have you been upset because of something that happened unexpectedly?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.3 In the last month, how often have you felt that you were unable to control the important things in your life?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.4 In the last month, how often have you felt nervous and “stressed”?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.5 In the last month, how often have you felt confident about your ability to handle your personal problems?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.6 In the last month, how often have you felt that things were going your way?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.7 In the last month, how often have you found that you could not cope with all the things that you had to do?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.8 In the last month, how often have you been able to control irritations in your life?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.9 In the last month, how often have you felt that you were on top of things?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.10 In the last month, how often have you been angered because of things that were outside of your control?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

Q4.11 In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?

- Never
- Almost Never
- Sometimes
- Fairly Often
- Very Often

End of Block: PSS Survey

Start of Block: Fear of COVID-19 Survey

Q5.1 Timing
Page Submit
Click Count

Q5.2
Please indicate your level of agreement or disagreement with the following statements:

I am most afraid of COVID-19.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.3 It makes me uncomfortable thinking about COVID-19.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.4 My hands become clammy when I think about COVID-19.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.5 I am afraid of losing my life because of COVID-19.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.6 When watching news and stories about COVID-19 on social media, I become nervous or anxious.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.7 I lose sleep because I'm worried about getting COVID-19.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.8 My heart races or palpitates when I think about getting COVID-19.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

End of Block: Fear of COVID-19 Survey

Start of Block: Video Quiz

Q6.1 Click on the bus design you like the best

Page Break

Q6.2 **Next, please watch 2 videos of bus travel at Texas A&M University.**
You will be asked three questions about what you watched in each of the videos.
Watch carefully, you can earn additional money for correct answers to the questions.

Page Break

Q6.3 Timing

Page Submit
Click Count

Q6.4 Video 1:

Page Break

Q6.5 Timing
Page Submit
Click Count

Q6.6 Do you have health concerns while waiting for the bus at the bus stop shown in the video?

- Extremely concerned
- Somewhat concerned
- Neither concerned nor unconcerned
- Somewhat unconcerned
- Extremely unconcerned

Q6.7 (Paid Question)
Referring to the video shown previously,
What was the weather condition on that day?

- Sunny
- Cloudy
- Windy
- Rainy

Q6.8 (Paid Question)
Referring to the video shown previously,
How many students were sitting on the first bench?

- 1
- 2
- 3
- 4

Page Break

Q6.9 Timing
Page Submit
Click Count

Q6.10 Video 2:

Page Break

Q6.11 Timing
Page Submit
Click Count

Q6.12 Do you have health concerns riding in the bus shown in the video?

- Extremely concerned
- Somewhat concerned
- Neither concerned nor unconcerned
- Somewhat unconcerned
- Extremely unconcerned

Q6.13 (Paid Question)
Referring to the video shown previously,
Was the driver wearing shorts?

- Yes
- No

Q6.14 (Paid Question)
Referring to the video shown previously,
At one point you observed a person with dyed hair color. What color was it?

- Orange
- Yellow
- Fuchsia/Purple
- Red

Q6.15 If you have any additional comments on travel, you are welcome to share them in the space below.

____

Page Break

Q6.16 Your final score is : **$(Paid Question Score)/4**
You will receive (**$16 + ${(Paid Question Score)}**) as your compensation.

Please raise your hand to call research personnel to note your final payment.

Thank you for your participation.

End of Block: Video Quiz

Appendix C. Validation of FCV Scale Results (Travel Survey Augmented with GSR)

Methodology

To measure the reliability of the items in the scale and to understand how consistent the items on a scale are to measure a concept, internal consistency reliability of the FCV-19 Scale was performed. As to the knowledge, this research being the first to use the English version of the FCV-19 Scale in a sample of U.S. college students after the pandemic, the validity of the scale was checked by conducting construct validity and exploratory factor analysis. Construct validity aids in ensuring that the measurement captures the intended outcome.

Statistical software SPSS version 29.0 was used to perform Cronbach's alpha, inter-item correlation, and corrected-item correlation to measure the internal consistency reliability of the scale. Cronbach's alpha measures how closely the items of the group are correlated and thus is generally considered the coefficient of consistency (UCLA: Statistical Consulting Group). The value of alpha can range from 0 to 1 with higher values indicating more reliability. The alpha value greater than equal to 0.80, a minimum range of values between 0.15 and 0.50 for inter-item correlation, and a minimum corrected item-total correlation of 0.30 is generally a recommended indicator of internal consistency reliability (Clark and Watson 2016, Field 2009). The factor solutions for the FCV-19 Scale have not always been consistent in the previous studies, thus, exploratory factor analysis (EFA) was performed for the scale on this study sample. EFA can be used to improve the interpretability of the variables in the scale. The principal axis factor analysis was performed using the SPSS Statistics software. The Kaiser-Meyer-Olkin (KMO) test was done to find how suitable the data was for the factor analysis. A value greater than or equal to 0.8 is recommended for the KMO measure to provide evidence of a sufficiently large sample size to run a factor analysis.

Results

The mean FCV-19 total score for the sample was 14.6 with a standard deviation of 5.4. The values for the three indicators were above the recommended cutoff by Clark and Watson and Field. The Cronbach's alpha value was 0.83 for the FCV-19 Scale, which depicted a relatively high correlation or consistency between the items in the scale. The inter-item correlation range showed moderate correlation with values ranging from 0.28 to 0.58 which is within the recommended limit. The corrected-item total correlation bolsters the reliability of the scale with all the values greater than or equal to 0.48. The overall results showed that the scale had moderate to good internal consistency reliability.

The KMO measure of sampling adequacy for the sample came out to be 0.81, demonstrating an appropriate sample size for EFA. Bartlett's Test of Sphericity had a Chi-Square value of 466.9 ($p<0.001$), representing a significant correlation between the variables in the scale. The principal axis factor analysis results are consistent with some of the research studies in past (Sakib et al., 2020; Alyami et al., 2020; Ahorsu et al., 2020) revealing a single-factor solution. The eigenvalue of 3.5 explained 50% of the variance in the Fear of COVID-19 scores. The factor loading results depicted moderately high factor loadings with a minimum value of 0.54. All these results combined showed that the Fear of COVID-19 Scale is unidimensional having a one-factor solution for a US college sample post-pandemic.

Appendix D. Raw Data for both Web Survey and Travel Survey Augmented with GSR

Table D1. Raw Demographics and Travel Survey Data Collected for Web Survey and Survey Augmented with GSR

Characteristic		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
Demographics			
Age	18~24	692	137
	25~34	2846	60
	35~44	1065	2
	45~54	1597	1
	Above 55	72	-
Ethnicity	White or Caucasian	3071	70
	Hispanic	769	24
	Black or African American	694	9
	Asian	590	91
	Native American or Alaskan Native	743	-
	Multiracial or Biracial	407	6
	Others	13	-
Gender	Female	2518	119
	Male	3702	81
	Others / No Answer	80	-
Annual household income	Less than $10,000	131	38
	$10,000 - $14,999	195	20
	15,000 ~ 24,999	945	23
	25,000 ~ 34,999	1207	22
	35,000 ~ 49,999	1062	22
	50,000 ~ 74,999	983	14

Characteristic		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
	75,000 ~ 99,999	815	10
	100,000 ~ 124,999	353	10
	$125,000 - $149,999	233	10
	$150,000 - $199,999	163	6
	More than $200,000	116	8
	Prefer not to answer	95	17
Current employment status	Full-Time	3267	6
	Part-Time	1220	49
	Student	701	142
	Homemaker	391	-
	Retired	354	-
	Unemployed	352	3
Contracted COVID-19	Yes	738	93
	No	4945	89
	Unsure	557	18
	Prefer not to say	50	-
Highest Level of Education	High School	735	16
	Some College	1755	76
	Associate \ Vocational \ Technical Degree	1606	7
	Bachelor's Degree	1578	52
	Master's or PHD	619	49
Days working from home in a week before COVID (March 2020)	0 days	946	148
	1–2 days	2363	29
	3–4 days	1793	5
	5 days	932	11
	6–7 days	264	7

Characteristic		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
People living in your household including yourself	1	212	53
	2	1682	30
	3	1936	30
	4	1484	64
	More than 4	982	23
Travel Survey			
Do you own/have access to a motor vehicle?	No	503	43
	Yes	5781	157
How often did you ride the bus/train (past)?	More than 10 trips a week	464	30
	6 to 10 trips a week	1729	40
	1 to 5 trips a week	1955	39
	1 to 4 trips a month	1465	34
	Less than 1 trips a month	453	22
	Never	222	35
Currently, how often do you ride the bus/train?	More than 10 trips a week	381	29
	6 to 10 trips a week	1499	32
	1 to 5 trips a week	1904	48
	1 to 4 trips a month	1570	36
	Less than 1 trips a month	690	38
	Never	245	17
After COVID-19, will you ride transit more, less or the same amount as before COVID-19?	Less	3184	45
	More	985	51
	Same	2123	104
Do you now ride transit more, less or the same amount as before COVID-19?	Less	2157	92
	More	1338	63
	Same	2805	45

Table D2. Raw Fear of COVID-19 Scale Data Collected for Web Survey and Survey Augmented with GSR

Fear of COVID-19 Scale Questionnaire		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
I am most afraid of COVID-19.	Strongly Disagree	809	51
	Somewhat Disagree	1298	59
	Neither Agree nor Disagree	1402	35
	Somewhat Agree	1875	44
	Strongly Agree	910	11
It makes me uncomfortable thinking about COVID-19.	Strongly Disagree	758	55
	Somewhat Disagree	1220	48
	Neither Agree nor Disagree	1375	34
	Somewhat Agree	2123	55
	Strongly Agree	821	8
My hands become clammy when I think about COVID-19.	Strongly Disagree	1083	132
	Somewhat Disagree	1355	36
	Neither Agree nor Disagree	1670	21
	Somewhat Agree	1651	10
	Strongly Agree	536	1
I am afraid of losing my life because of COVID-19.	Strongly Disagree	892	86
	Somewhat Disagree	1086	42
	Neither Agree nor Disagree	1249	28
	Somewhat Agree	1945	37
	Strongly Agree	1123	7
When watching news and stories about COVID-19 on social media, I become nervous or anxious.	Strongly Disagree	819	34
	Somewhat Disagree	1338	45
	Neither Agree nor Disagree	1431	23
	Somewhat Agree	2023	89
	Strongly Agree	687	9

Fear of COVID-19 Scale Questionnaire		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
I lose sleep because I'm worried about getting COVID-19.	Strongly Disagree	1170	163
	Somewhat Disagree	1458	28
	Neither Agree nor Disagree	1464	5
	Somewhat Agree	1655	3
	Strongly Agree	533	1
My heart races or palpitates when I think about getting COVID-19.	Strongly Disagree	1032	135
	Somewhat Disagree	1281	34
	Neither Agree nor Disagree	1464	0
	Somewhat Agree	1811	15
	Strongly Agree	692	16

Table D3. Raw Perceived Stress Scale Data Collected for Web Survey and Survey Augmented with GSR

Perceived Stress Scale Questionnaire		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
In the last month, how often have you been upset because of something that happened unexpectedly?	Never	718	10
	Almost Never	1500	39
	Sometimes	2662	101
	Fairly Often	1099	41
	Very Often	316	9
In the last month, how often have you felt that you were unable to control the important things in your life?	Never	694	11
	Almost Never	1629	40
	Sometimes	2374	88
	Fairly Often	1222	45
	Very Often	376	16
In the last month, how often have you felt nervous and “stressed”?	Never	709	11
	Almost Never	1238	40

Perceived Stress Scale Questionnaire		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
	Sometimes	2420	88
	Fairly Often	1410	45
	Very Often	517	16
In the last month, how often have you felt confident about your ability to handle your personal problems?	Never	298	0
	Almost Never	844	11
	Sometimes	2428	72
	Fairly Often	1677	81
	Very Often	1049	36
In the last month, how often have you felt that things were going your way?	Never	629	1
	Almost Never	1163	19
	Sometimes	2479	98
	Fairly Often	1520	68
	Very Often	507	14
In the last month, how often have you found that you could not cope with all the things that you had to do?	Never	715	16
	Almost Never	1562	72
	Sometimes	2550	77
	Fairly Often	1131	25
	Very Often	336	10
In the last month, how often have you been able to control irritations in your life?	Never	645	2
	Almost Never	1235	10
	Sometimes	2410	73
	Fairly Often	1517	92
	Very Often	489	23
In the last month, how often have you felt that you were on top of things?	Never	616	4
	Almost Never	1311	24
	Sometimes	2407	95
	Fairly Often	1509	60
	Very Often	453	17

Perceived Stress Scale Questionnaire		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
In the last month, how often have you been angered because of things that were outside of your control?	Never	660	15
	Almost Never	1500	59
	Sometimes	2438	67
	Fairly Often	1299	43
	Very Often	398	16
In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?	Never	752	28
	Almost Never	1580	67
	Sometimes	2383	70
	Fairly Often	1160	25
	Very Often	422	10

Table D4. Important Factors for Personal Motor Vehicle Use Raw Data Gathered for Web Survey and GSR-Enhanced Survey

Importance of Factors for using your personal motor vehicle for daily travel?		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
I don't have to wait for the bus	Not at all Important	555	2
	Slightly Important	1032	9
	Moderately important	1398	27
	Very important	1648	55
	Extremely important	1133	64
Comfort of my motor vehicle	Not at all Important	562	13
	Slightly Important	981	22
	Moderately important	1404	34
	Very important	1653	42
	Extremely important	1165	46

Importance of Factors for using your personal motor vehicle for daily travel?		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
Shorter travel time	Not at all Important	548	3
	Slightly Important	928	10
	Moderately important	1458	21
	Very important	1644	59
	Extremely important	1188	64
Cleanliness of the vehicle	Not at all Important	543	20
	Slightly Important	977	35
	Moderately important	1443	46
	Very important	1636	35
	Extremely important	1164	21
Lower chances of catching COVID	Not at all Important	637	33
	Slightly Important	941	39
	Moderately important	1162	36
	Very important	1526	26
	Extremely important	1499	23
Can run errands/shopping at any time	Not at all Important	565	5
	Slightly Important	969	2
	Moderately important	1417	18
	Very important	1653	53
	Extremely important	1161	79
The bus/train does not go to the places I need to go	Not at all Important	631	5
	Slightly Important	966	16
	Moderately important	1360	32
	Very important	1657	41
	Extremely important	1151	63

Table D5. Likeliness to Travel again by Bus Raw Data Gathered for Web Survey and GSR-Enhanced Survey

Likeliness of Traveling again by Bus in following scenarios		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
If most of the population is vaccinated	Extremely unlikely	9	1
	Somewhat unlikely	31	2
	Neither likely nor unlikely	106	4
	Somewhat likely	271	19
	Extremely likely	146	15
Proper cleanliness and social distancing is maintained	Extremely unlikely	8	1
	Somewhat unlikely	41	0
	Neither likely nor unlikely	100	11
	Somewhat likely	269	13
	Extremely likely	145	16
Parking cost is increased	Extremely unlikely	20	2
	Somewhat unlikely	94	3
	Neither likely nor unlikely	114	5
	Somewhat likely	228	18
	Extremely likely	107	13
If the buses can reach more destinations	Extremely unlikely	11	2
	Somewhat unlikely	62	1
	Neither likely nor unlikely	102	2
	Somewhat likely	249	16
	Extremely likely	139	20
If the buses run more often	Extremely unlikely	17	2
	Somewhat unlikely	80	2
	Neither likely nor unlikely	125	6
	Somewhat likely	235	12
	Extremely likely	106	19

Likeliness of Traveling again by Bus in following scenarios		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
I must travel to the office more because I am working from home less	Extremely unlikely	21	3
	Somewhat unlikely	87	11
	Neither likely nor unlikely	134	9
	Somewhat likely	216	11
	Extremely likely	105	7

Table D6. Obstacles to using Transit Raw Data for Web Survey and GSR-Enhanced Survey

Obstacles that keep you from using the bus/train more often?	Number of Responses in Each Category	
	Original Survey Responses	GSR+Survey Responses
Bus service is not in my area or can't reach a desired destination	1229	49
Travel time for the bus service is too unreliable	1331	64
Need my vehicle for making trips or running errands during the day	865	65
Fear of getting COVID	2135	36
It makes me feel unsafe to walk to or wait at a bus stop	1115	5
Long waiting time or high trip delays in the bus service	2216	87
I don't have information about the bus service / it is difficult to use the bus service	785	20
I drive my own vehicle	1395	100
I use other modes (i.e., walking, bicycle, scooter, etc.)	1010	70
I work more often from home	887	31

Table D7. Level of Concern Watching the Videos Raw Data for Web Survey and GSR-Enhanced Survey

Concern/Comfort level while watching the first-perspective videos		Number of Responses in Each Category	
		Original Survey Responses	GSR+Survey Responses
Video 1: Bus Stop Video	Extremely uncomfortable/concerned	827	3
	Somewhat uncomfortable/concerned	1815	71
	Neither comfortable/unconcerned nor uncomfortable/concerned	1524	47
	Somewhat comfortable/unconcerned	1322	39
	Extremely comfortable/unconcerned	718	40
Video 2: Bus Ride Video	Extremely uncomfortable/concerned	993	30
	Somewhat uncomfortable/concerned	1850	97
	Neither comfortable/unconcerned nor uncomfortable/concerned	1463	24
	Somewhat comfortable/unconcerned	1213	25
	Extremely comfortable/unconcerned	693	24

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