



**Center for Advanced Multimodal Mobility  
Solutions and Education**

**Project ID: 2022 Project 12**

**INVESTIGATING THE IMPACT OF COVID-19  
PANDEMIC OUTBREAK ON BIKE SHARE USAGE AND  
RIDERSHIP: A CASE STUDY IN HOUSTON**

**Final Report**

by

Mehdi Azimi, Ph.D., P.E. (ORCID ID: <https://orcid.org/0000-0001-5678-0323>)  
Associate Professor, Department of Transportation Studies, Texas Southern University  
Phone: 1-713-313-1293; Email: [Mehdi.Azimi@tsu.edu](mailto:Mehdi.Azimi@tsu.edu)

Mustafa Muhammad Wali (ORCID ID: <https://orcid.org/0000-0002-2812-8052>)  
Graduate Research Assistant, Department of Transportation Studies, Texas Southern University  
Phone: 1-713-313-1854; Email: [m.muhammad3150@student.tsu.edu](mailto:m.muhammad3150@student.tsu.edu)

Yi Qi, Ph.D. (ORCID ID: <https://orcid.org/0000-0002-6314-2626>)  
Professor and Chair, Department of Transportation Studies, Texas Southern University  
Phone: 1-713-313-6809; Email: [Yi.Qi@tsu.edu](mailto:Yi.Qi@tsu.edu)

for

Center for Advanced Multimodal Mobility Solutions and Education  
(Cammse @ UNC Charlotte)  
The University of North Carolina at Charlotte  
9201 University City Blvd  
Charlotte, NC 28223

**August 2024**



## **ACKNOWLEDGEMENTS**

This project was funded by the Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE @ UNC Charlotte), one of the Tier I University Transportation Centers that were selected in this nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT), under the FAST Act. The authors are also very grateful for all of the time and effort spent by DOT and industry professionals to provide project information that was critical for the successful completion of this study. The authors would also like to thank Houston BCycle for their assistance with data collection.

## **DISCLAIMER**

The contents of this report reflect the views of the authors, who are solely responsible for the facts and the accuracy of the material and information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation University Transportation Centers Program in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof. The contents do not necessarily reflect the official views of the U.S. Government. This report does not constitute a standard, specification, or regulation.



# Table of Contents

|  |           |
|--|-----------|
| <b>EXECUTIVE SUMMARY .....</b>   | <b>xi</b> |
| <b>Chapter 1. Introduction .....</b>                                       | <b>1</b>  |
| 1.1 Problem Statement .....  | 1         |
| 1.2 Objectives .....   | 5         |
| 1.3 Report Overview .....  | 5         |
| <b>Chapter 2. Literature Review .....</b>                                  | <b>7</b>  |
| 2.1 Introduction.....  | 7         |
| 2.2 Bike Sharing Systems During the COVID-19 Pandemic .....                | 7         |
| 2.3 Determinant Factors in Bicycle Use Before and During the Pandemic..... | 8         |
| 2.4 Summary .....  | 9         |
| <b>Chapter 3. Methodology .....</b>  | <b>12</b> |
| 3.1 Introduction.....  | 12        |
| 3.2 Solution Framework and its Distinct Features .....                     | 12        |
| 3.3 Variable Selection.....  | 14        |
| 3.4 Model Selection .....  | 16        |
| 3.5 Negative Binomial Regression Model .....                               | 16        |
| <b>Chapter 4. Analysis Results .....</b>                                   | <b>19</b> |
| 4.1 Introduction.....  | 19        |
| 4.2 Descriptive Analysis .....   | 19        |
| 4.3 Negative Binomial Regression Model Results .....                       | 26        |
| <b>Chapter 5. Summary and Conclusions .....</b>                            | <b>29</b> |
| 5.1 Introduction.....  | 29        |
| 5.2 Summary and Conclusions .....  | 29        |
| 5.3 Directions for Future Research .....                                   | 30        |
| <b>References .....</b>  | <b>32</b> |



## List of Figures

|   |    |
|---|----|
| Figure 1.1: Station-Based Bikeshare (Source: Houston Chronicles, 2018).....   | 1  |
| Figure 1.2: Smart-Bike Bikeshare (Source: BCycle, 2016).....  | 2  |
| Figure 1.3: Dockless Bikeshare (Source: Streetsblog USA, 2018) .....  | 2  |
| Figure 1.4: Houston Bikeshare Stations Map (Source: Houston BCycle, 2023).....                                      | 3  |
| Figure 3.1: Houston Weather Stations (Source: NOAA, 2023).....  | 14 |
| Figure 4.1: Daily Ridership of the Houston Bikeshare Program, 2020 .....  | 19 |
| Figure 4.2: Daily COVID-19 Case Counts in Houston, 2020 .....   | 20 |
| Figure 4.3: Daily Houston Bikeshare Trips and COVID-19 Case Counts in 2020 .....                                    | 20 |
| Figure 4.4: Houston Bikeshare Ridership by Trip Duration Categories in 2019.....                                    | 21 |
| Figure 4.5: Houston Bikeshare Ridership by Trip Duration Categories in 2020 and Daily<br>COVID-19 Case Counts ..... | 22 |
| Figure 4.6: Daily Average Trip Durations and COVID-19 Case Counts for Houston<br>Bikeshare in 2020 .....            | 22 |
| Figure 4.7: Houston Bikeshare Daily Trips During Peak and Off-Peak Hours in 2019.....                               | 23 |
| Figure 4.8: Houston Bikeshare Daily Trips During Peak and Off-Peak Hours and<br>COVID-19 Case Counts in 2020 .....  | 24 |
| Figure 4.9: Daily Trips by Members and Non-Members of Houston Bikeshare in 2019 .....                               | 24 |
| Figure 4.10: Daily Trips by Members and Non-Members of Houston Bikeshare and<br>COVID-19 Case Counts in 2020 .....  | 25 |
| Figure 4.11: Houston Bikeshare Daily Ridership in Relation to Temperature (a) and<br>Rainfall (b) in 2020.....      | 26 |



## List of Tables

|   |    |
|---|----|
| Table 3.1: Multicollinearity Test Results (Variance Inflation Factor) .....                                   | 15 |
| Table 3.2: Descriptive Statistics of Variables .....  | 15 |
| Table 4.1: Negative Binomial Regression Results .....   | 26 |
| Table 4.2: Negative Binomial Regression Results Considering Three Independent<br>Variables .....              | 27 |
| Table 4.3: Model Results - Estimated Coefficients, Marginal Effects, and Incidence Rate<br>Ratios (IRR) ..... | 27 |



## **EXECUTIVE SUMMARY**

A bikeshare system is a transportation service where bicycles are available for shared use by individuals for short-term rentals at low or no cost. It offers an affordable, healthy, and environmentally friendly alternative for users, while also serving as a solution for those without personal vehicles and helping to reduce the rise in private car usage.

This study aimed to investigate the impact of the COVID-19 pandemic on bikeshare ridership, with a case study focused on the City of Houston. The data used in this study include bikeshare ridership records for 2019 and 2020, COVID-19 case data for Harris County residents in 2020, as well as temperature and precipitation data for Houston for the years 2019 and 2020. The methodology involved both descriptive analysis and the application of Negative Binomial regression modeling to explore the relationships between ridership (the dependent variable) and several independent variables.

The descriptive analysis revealed an overall increase in bikeshare ridership during 2020, the COVID-19 period. Longer-duration trips in 2020 were significantly more frequent compared to 2019, with most trips occurring during off-peak hours, followed by evening and morning peaks. Additionally, regression analysis showed that the COVID-19 pandemic had a statistically significant positive effect on average daily ridership, with COVID-19 case counts positively correlated with ridership levels. The weekend indicator demonstrated the strongest positive impact on ridership, while temperature had no statistically significant effect. In contrast, precipitation showed the strongest statistically significant negative impact on average daily ridership.



# Chapter 1. Introduction

## 1.1 Problem Statement

Bike sharing has emerged as an innovative public transportation system that allows individuals to rent bicycles for short-distance trips. Shaheen et al. (2015) define bikeshare as a system that provides users with access to bicycles on an as-needed basis through a network of stations, typically concentrated in urban areas. These systems generally feature a network of stations across a city or region, where bikes can be rented and returned. Users can rent a bike by purchasing a pass or membership, and then unlock a bike from a station using a credit card or smartphone app. Bikes can be returned to any station in the system, offering flexibility and convenience. Bikeshare systems have gained significant popularity in recent years as a healthy, sustainable, and cost-effective alternative to other modes of transportation. They help reduce traffic congestion and air pollution, while also promoting active transportation.

Bikeshare systems vary in size, pricing, and features. Some are operated by public agencies, while others are managed by private companies. In certain systems, bikes must be returned to a designated station, while others allow users to leave bikes at any public bike rack. Additionally, some systems offer electric-assist bikes to make longer or uphill trips easier. There are several types of bikeshare systems, including:

**Station-based Bikeshare:** The most common type, involving a network of stations where users can pick up and drop off bikes.



Figure 1.1: Station-Based Bikeshare (Source: Houston Chronicles, 2018)

**Smart-Bike Bikeshare:** This system uses bikes equipped with smart locks that allow them to be locked and unlocked without the need for a specific station, adding flexibility for users.



**Figure 1.2: Smart-Bike Bikeshare (Source: BCycle, 2016)**

**Dockless Bikeshare:** This system allows users to pick up and drop off bikes anywhere, using a smartphone app to locate and unlock them. While convenient, it can sometimes lead to issues with bike parking and clutter.

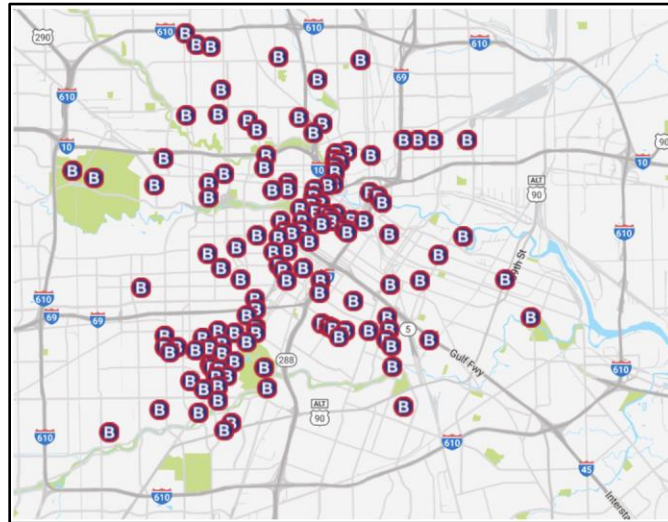


**Figure 1.3: Dockless Bikeshare (Source: Streetsblog USA, 2018)**

In Houston, Houston BCycle, a local 501(c)(3) nonprofit organization, operates the city's bikeshare system with support from the City of Houston, local businesses, and other sponsors. Launched in 2012 with just three stations and 18 bikes, the program has since expanded

significantly, enhancing connectivity across the city. By 2021, Houston BCycle had grown its network to 153 stations with over 1,000 bicycles, including 100 electric bikes. These stations are strategically located throughout the city, primarily within the I-610 loop, and include popular tourist destinations, parks, and major employment centers.

The system offers a variety of bikes, including traditional and electric-assist models, providing users with flexible and convenient transportation options. Riders can purchase a membership or pass to unlock bikes from any station and return them at any other station, making it easy to navigate the city.



**Figure 1.4: Houston Bikeshare Stations Map (Source: Houston BCycle, 2023)**

Houston BCycle's goal is to provide a healthier, more sustainable, and equitable transportation option for the people of Houston. The system is designed to promote active transportation and reduce dependence on cars, helping to improve air quality, reduce traffic congestion, and enhance public health. Houston BCycle also offers corporate memberships and partnerships with local organizations to encourage bikeshare use among employees, students, and other groups. A notable initiative was its bikeshare program in collaboration with the Houston Public Library, allowing customers to check out a bike for up to 24 hours. Overall, the bikeshare system is a convenient and flexible option for short trips around the city, accessible to people of various income levels, ages, and abilities.

As of 2021, according to the U.S. Census Bureau's Population Estimates Program, Houston is the fourth most populous city in the United States, with an estimated population of 2.3 million. It is also one of the fastest-growing cities, with a 2020 growth rate of 1.08%, according to the World Population Review. Houston is a diverse and multicultural city, with significant African American, Hispanic, Asian, and White populations. The city's economy is equally diverse, with major sectors including oil and gas, healthcare, education, and government. This economic and population diversity, coupled with the city's large geographic area, makes urban planning and development complex and multifaceted. Houston's urban layout is characterized by relatively low density and sprawl, partly due to the city's lack of zoning

regulations, which has allowed for a mix of land uses. Residential, commercial, and industrial areas often exist in close proximity, creating a unique urban landscape. However, the city has been criticized for its lack of walkability and bike-friendly infrastructure, which makes it difficult for people to navigate without a car. In response, Houston has been actively working to improve walkability and cycling infrastructure in recent years, and the bikeshare program has played a key role in promoting active transportation.

Houston's rapid growth has also led to challenges such as traffic congestion, air quality issues, and flooding. To address these, the city has implemented various transportation and land use policies aimed at reducing congestion, improving air quality, and mitigating flood risks. Houston has also been promoting sustainable development and reducing its environmental impact through initiatives like the green building ordinance and the adoption of a climate action plan, which outlines strategies for reducing greenhouse gas emissions and adapting to climate change.

The COVID-19 pandemic dramatically altered travel behavior across North America. Ridership on major public transit systems dropped as stay-at-home orders were implemented to enable social distancing and reduce the spread of the virus. A survey conducted by TransLoc (2021) indicated that 74% of Americans used public transit at least twice a week before the pandemic. However, according to the American Public Transportation Association (APTA), ridership declined by 79% in 2020 compared to 2019. Although ridership began to recover slightly between June and December 2020, it remained about 65% below pre-pandemic levels. In the Houston region, the Air Alliance Houston, LINK Houston, and Texas Southern University conducted a study assessing the impact of the pandemic on transit, showing a significant reduction in vehicle miles traveled (VMT). Harris County, for instance, experienced a 79% drop in VMT in April 2020 compared to the January average. The city's transit agency also saw a 40% decrease in public transportation usage due to concerns over virus transmission (Rozen, 2021).

The pandemic also had a major impact on bikeshare systems. During the initial stages, many systems either shut down or reduced services, leading to a decline in ridership. However, as restrictions were eased and people sought alternatives to crowded buses and trains, bikeshare ridership began to recover, with some systems even experiencing a surge in use. Systems in urban areas and those reliant on tourism were more heavily affected than those serving local ridership. To adapt, many bikeshare operators implemented safety measures such as increased bike and station sanitization and encouraged mask usage and social distancing. The pandemic emphasized the importance of bike sharing as a flexible and resilient transportation option during crises, highlighting the need for continued investment in sustainable transit infrastructure.

Houston's bikeshare program continues to promote sustainability and accessibility, addressing the city's transportation challenges. The COVID-19 pandemic has emphasized the necessity of sustainable transit systems capable of withstanding disruptions. Understanding the impact of the pandemic on bikeshare systems is essential for researchers and policymakers. Studies that examine how factors such as the pandemic and weather conditions influence bikeshare ridership in Houston provide valuable insights for developing resilient and sustainable transportation solutions.

## 1.2 Objectives

This study aims to investigate the impact of the COVID-19 pandemic on bikeshare ridership, using Houston as a case study. The research is crucial as it sheds light on changes in travel behavior, particularly in the use of biking in large metropolitan areas during a pandemic like COVID-19. The study has the following objectives:

- Collect the necessary data for the research.
- Illustrate how the COVID-19 pandemic affected bikeshare ridership.
- Apply a model to examine the relationship between the number of COVID-19 cases and bikeshare ridership.
- Analyze how environmental factors, such as weather conditions, influence bikeshare ridership in Houston.
- Demonstrate how the proposed methodology can offer new insights into these relationships.

## 1.3 Report Overview

The remainder of this report is organized as follows: Chapter 2 presents a literature review of existing research on the impacts of COVID-19 on bikeshare systems, as well as the various methodologies used in similar studies. Chapter 3 offers a detailed description of the data and methodology, introducing the Negative Binomial regression model and discussing the variables considered in the ridership and COVID-19 data analysis. Additionally, it explains the data collection process, including data extraction and description. Chapter 4 presents the findings from the descriptive analysis, including graphs, and discusses patterns, trends, relationships, and interpretations of the Negative Binomial regression results. Finally, Chapter 5 provides conclusions and offers recommendations for future research.



## Chapter 2. Literature Review

### 2.1 Introduction

The literature review for this study was conducted from multiple perspectives to establish the context for the proposed research, with a particular focus on how the COVID-19 pandemic impacted bikeshare ridership in metropolitan areas. This chapter provides an overview of previous research studies related to the topic and summarizes the key findings from those studies. Research on the impacts of COVID-19 on ridership, trip duration, the built environment, public transit, socioeconomic factors, as well as temporal, spatial, weather influences, and resiliency have become increasingly common since the onset of the pandemic.

### 2.2 Bike Sharing Systems During the COVID-19 Pandemic

Berezvai (2022) used panel regression methods to investigate how the COVID-19 pandemic impacted bike-sharing ridership in Budapest, Hungary. The study aimed to isolate the effects of mobility restrictions and government policies on ridership and assess whether any long-term positive effects on bike-sharing were observed. The first COVID-19 case in Hungary was confirmed on March 4, 2020, and stringent measures were implemented shortly after. Universities switched to online learning by March 12, followed by primary and secondary schools on March 16. At the same time, the fare for Budapest's bike-sharing system was drastically reduced to €0.30 for a monthly pass. Using data on individual trips from 2019 and 2020, the author performed descriptive analysis and regression modeling to examine the effects of these measures on new users and the churn rate. The results indicated that both mobility restrictions and government interventions had significant positive impacts on bike-sharing usage, particularly in residential areas near public parks. Both descriptive and regression analyses suggested that bike-sharing use increased during the pandemic in Budapest.

Bike-sharing is a popular transportation mode for commuting, leisure, and recreational activities. Vo et al. (2022) analyzed trip volume and duration patterns among members and non-members of five U.S. bike-sharing systems: Capital Bikeshare (Washington, D.C.), Divvy (Chicago), Bluebikes (Boston), Nice Ride (Minneapolis), and Metro Bike Share (Los Angeles). Using linear regression models, the authors evaluated how the pandemic impacted user behavior. Results indicated that member ridership generally did not return to pre-pandemic levels, except in Minneapolis. For non-members, only Washington, D.C. experienced a statistically significant increase. Both members and non-members took longer trips during the pandemic. These findings provide valuable guidance for city authorities and bike-share operators to develop plans that address transportation needs during disruptions like pandemics or natural disasters.

COVID-19 prompted unprecedented measures that significantly altered transportation systems and travel habits. Li et al. (2021) examined the effects of lockdown policies on public bike-sharing in London using a segmented regression approach based on an interrupted time series design. The study analyzed data from the London Cycle Hire (LCH) system from January 2019 to June 2020. The boroughs with LCH stations were categorized into highly and less-infected areas, and regression models were applied to assess the impacts of lockdown measures. The results showed a sharp decline in LCH usage during lockdown, with varying impacts

depending on station proximity to parks, hospitals, and railway stations. While usage near train stations dropped significantly, trips to parks increased during lockdown easing.

Padmanabhan et al. (2021) assessed the effects of COVID-19 on bike-sharing systems in New York, Boston, and Chicago using correlation analysis and a random parameter least squares regression model. Data from October 2019 to May 2020 enabled a comparison of pre- and during-pandemic trends. The results revealed a decrease in bike trips but an increase in trip duration. NYC had consistently shorter trip durations compared to Boston and Chicago, possibly due to its sprawling urban layout.

Wang and Noland (2021) studied changes in bike-share usage in Brooklyn during the pandemic using data from Citi Bike from September 2019 to September 2020. They employed Thiessen polygons to analyze station service areas. The results indicated a shift from commuting to leisure trips, with casual users taking more trips in September 2020 than in September 2019. Trip durations also increased, potentially due to a shift from public transit to bike-sharing. Kim (2021) investigated the impact of COVID-19 on Seoul's bike-sharing system using a combination of descriptive and quantitative analyses. The study found that the number of daily confirmed COVID-19 cases affected bike rental demand, with rentals decreasing as case numbers increased. However, higher social distancing levels led to increased bike rentals, possibly due to limited indoor activities and more people seeking outdoor alternatives. Bike rentals in residential areas rose, while those in commercial areas declined.

Teixeira and Lopes (2020) analyzed the impact of COVID-19 on New York City's transportation system, focusing on the Citi Bike system and the subway. Using a combination of descriptive statistics, Mann-Whitney U tests, and Ordinary Least Squares (OLS) regression analysis, the study examined changes in average trip duration and mode shifts. The results showed that bike-sharing was more resilient than the subway system, experiencing less ridership loss and an increase in trip duration. A modal shift from the subway to bike-sharing was observed, indicating that some users switched to bikes during the pandemic.

### **2.3 Determinant Factors in Bicycle Use Before and During the Pandemic**

Public bicycles emerged as a pandemic-resistant mode of transportation during the COVID-19 outbreak. Sung (2023) examined daily bike-sharing ridership and identified differences in the influence of various determinants, such as weather conditions, non-seasonal events, and supply and demand, during the pandemic compared to pre-pandemic periods. The study analyzed bike-sharing ridership data in Seoul over 1,826 days, from 2017 to 2021, using a customized causal impact inference model based on the Bayesian Structural Time Series (BSTS) model. Despite the pandemic, public bicycles continued to be widely used in densely populated Seoul. The study found that, compared to the pre-pandemic period, public bicycle usage was not significantly affected on days with mild weather, including those with low levels of snow, rain, and wind. Similarly, non-seasonal events, such as weekdays, public holidays, and traditional Korean holidays, did not significantly affect usage. However, during the pandemic, public bikes were primarily used for leisure and exercise rather than commuting, suggesting that bike-sharing can be a safe and viable travel option during pandemics.

In cities worldwide, bike-sharing systems have been introduced to promote health, economic sustainability, and environmental benefits. Bustamante et al. (2022) identified a comprehensive set of factors that predict bike-sharing usage, which may have shifted during the COVID-19 pandemic in Barcelona. The study analyzed trips between stations from January 1, 2019, to December 31, 2020, using probabilistic machine learning in a quasi-experimental research design. Various variables, such as trip characteristics, day types, infrastructure, weather, socio-demographics, and land use, were considered. The study found that while overall bike-sharing usage increased during the pandemic, fewer trips were taken during summer months and the December holiday season. Notably, bike-related infrastructure, trip distance, and neighborhood income levels were the most relevant factors influencing bike-sharing usage both before and during the pandemic.

In Seoul, ridership increased during the pandemic, particularly among commuters and recreational users. Jiao et al. (2022) analyzed changes in bike-sharing patterns in Seoul using data from March 1, 2019, to June 30, 2020. The study applied negative binomial panel regression models to evaluate the impacts of climate, transportation, land use, social factors, and COVID-19 on bike-sharing ridership across 25 districts over 488 days. The results showed that despite the pandemic, people used bike-sharing services more frequently and for longer durations after the first COVID-19 case was reported in January 2020. The findings offered valuable insights for public bike transportation policies and the role of micromobility in the post-COVID era.

Data-driven analysis is essential for understanding bike-sharing mobility patterns. Albuquerque et al. (2021) performed a data-driven analysis of Lisbon's bike-sharing system to assess station and trip activity patterns. They employed the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, following the extraction, transformation, and visualization/loading (ETL) process to ensure accurate and clean data. The analysis revealed that the highest number of bike-sharing trips in Lisbon occurred during weekday afternoons in 2018, and weather conditions significantly influenced travel behavior. Most trips were concentrated in areas with a high density of offices and universities. Due to limited data for 2019 and 2020, a full spatiotemporal analysis could not be conducted; however, correlation analysis showed a relationship between urban mobility patterns and the usage of Lisbon's bike-sharing system during the pandemic.

Kurkcu et al. (2021) studied the impact of COVID-19 on bicycle usage in Colorado counties by analyzing bike-sharing systems and county-level COVID-19 data. The study also considered socioeconomic data from each station catchment area. Using Partial Least Squares Regression (PLSR) due to limited data, the authors analyzed the relationship between changes in bicycle usage and socioeconomic factors related to the pandemic. The results indicated that average income, education level, and total population were the most significant factors influencing the transition from the pandemic period to the normalization phase. Higher income and education levels positively impacted bicycle usage, while total population had a negative effect.

## **2.4 Summary**

Previous studies have examined the influence of factors such as trip characteristics, infrastructure, weather conditions, user demographics, and land use on bike-sharing ridership. However, a comprehensive understanding of how COVID-19, temporal variables, and weather

conditions affect bike-sharing system usage in the City of Houston remains limited. Our research provides important insights into bike-sharing ridership during the COVID-19 pandemic. This study aims to fill that gap by analyzing the significance of COVID-19, temporal, and weather factors in predicting bike-sharing usage.

Many previous studies on bike-sharing ridership rely on surveys, observations, or experiments conducted in specific locations, which can limit their ability to capture a complete picture of mobility across an entire city. To overcome this limitation, our study uses ridership data to analyze bike-sharing system usage in Houston, enabling us to draw conclusions based on real-world data rather than on samples. This approach allows us to more accurately determine the impacts of COVID-19, temporal variations, and weather conditions on bike-sharing ridership across the entire population of users.

Additionally, by comparing the periods before and after the COVID-19 outbreak, which significantly disrupted transportation systems and social behaviors, we can assess whether the factors influencing bike-sharing ridership have changed due to the pandemic. This comparative approach will help us identify whether the significance of these factors shifted as the pandemic evolved. Understanding the impact of the COVID-19 pandemic on bike-sharing systems is crucial for both researchers and policymakers. Researchers can use these insights to study how disruptive events affect urban mobility, while policymakers can leverage this information to better prepare cities for future crises and enhance their resilience.



## Chapter 3. Methodology

### 3.1 Introduction

This chapter outlines the methodology used in this research. To achieve the study's goals and objectives, it provides a detailed explanation of the data, the variable selection process, and the model chosen to analyze the count data. The data description includes information on the data sources, the data cleaning procedures, and the transformations applied during the study. In the variable selection process, relevant variables were identified, while those deemed unnecessary were excluded. This chapter establishes the groundwork for the subsequent analysis and interpretation of the results.

### 3.2 Solution Framework and its Distinct Features

The bikeshare system in Houston is operated by Houston BCycle, a local nonprofit organization. Launched in May 2012 with just three bike stations and 18 bicycles, the system has expanded to 1,000 bikes across 153 stations by 2021, including the addition of 100 electric bikes. The bikeshare ridership data used in this study was provided by Houston BCycle. The original dataset for 2019 and 2020 included detailed information for each bicycle trip, such as:

- trip ID
- user program name
- user ID
- user role (RFID card member or non-RFID card member)
- user city
- user state
- user zip code
- user country
- membership type (annual membership, single-use pass, or monthly membership)
- bike ID
- bike type
- check-out kiosk name
- return kiosk name
- trip duration (minutes)
- adjusted trip duration (minutes)
- usage fee
- adjustment flag
- distance traveled
- estimated carbon offset
- estimated calories burned
- check-out date (local)
- return date (local)

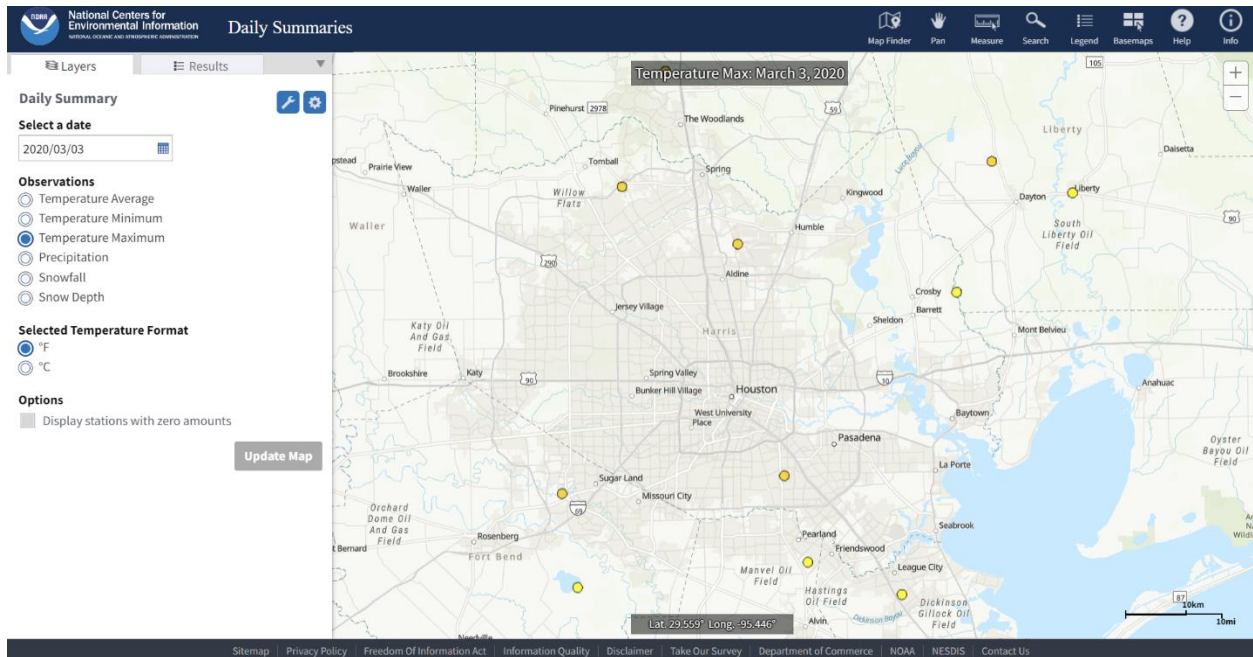
- check-out time (local)
- return time (local)
- trips over 30 minutes
- local program flag
- trip route category (round trip or one way)
- trip program name

For this study, trips with a duration of one minute or less were excluded, as they were considered too short to be valid trips. During data processing and cleaning, key attributes used included "checkout kiosk name" and "duration." Each trip's duration was extracted from the "duration" field, and trips were tallied based on the "checkout date (local)" field. The "checkout time (local)" attribute was also used to capture the timing of each trip. For descriptive analysis and analytical modeling, various formulas, filters, and Pivot Table functions in Microsoft Excel were employed to extract relevant data. The following attributes were ultimately selected for the analysis:

- user role (RFID card member or non-RFID card member)
- check-out kiosk name
- trip duration (minutes)
- check-out date (local)
- check-out time (local)

Daily COVID-19 case data for Houston were obtained from the Harris County and City of Houston COVID-19 Data Hub. This comprehensive resource, an initiative by local government, provides up-to-date information on the pandemic, including the number of cases, deaths, hospitalizations, and vaccination rates in the Houston metropolitan area. The dataset used in this study included attributes such as object ID, date, total cases, new cases, old cases, source (All, Harris County, and Houston), and date labels. According to reports, the first positive cases in Harris County and the City of Houston were reported on March 5, 2020, and April 2, 2020, respectively. The daily reported cases for Houston in 2020 were extracted using Microsoft Excel for the analysis.

Temperature and precipitation data for the study were downloaded from the National Oceanic and Atmospheric Administration (NOAA) website for each day in 2019 and 2020. The Houston William P. Hobby Airport weather station, the closest station to the bikeshare system, was used as the primary data source (Figure 3.1). The daily temperature data included both maximum and minimum values, from which daily average temperatures were calculated. The precipitation data reflected the amount of rainfall (in inches) recorded on each day.



**Figure 3.1: Houston Weather Stations (Source: NOAA, 2023)**

To assess the pandemic's impact on various parameters, several studies have used quantitative indicators to measure public fear of COVID-19. Qi et al. (2022) developed a composite index to gauge public fear levels for their model, revealing that heightened public fear in metropolitan areas significantly contributed to reductions in public transit ridership. Similarly, Liu et al. (2020) employed the Google search trend index for the keyword 'Coronavirus' to measure public awareness and concern about COVID-19.

In this study, the reported cases index was used to represent public fear of COVID-19 in the study area. Given the temporal lag between COVID-19 infections and their effect on daily ridership, a 14-day lag was considered appropriate to capture this "fear factor." Additionally, data from mid-November to the end of December 2020 was excluded from the modeling to eliminate the effects of major holidays, including Thanksgiving, Christmas, and New Year.

### 3.3 Variable Selection

The goal of this study is to investigate how bikeshare ridership was affected by the COVID-19 pandemic. To achieve this, the relationship between bikeshare ridership and several variables - such as daily COVID-19 cases, day of the week (weekday or weekend), and weather conditions (temperature and precipitation) - must be examined. In this analysis, bikeshare ridership is selected as the dependent variable, while COVID-19 daily cases, weekend indicator, temperature, and precipitation are chosen as the independent variables.

During the variable selection process, it is essential to conduct a multicollinearity test to assess the relationships among the independent variables. This step helps to minimize potential errors in the model and ensures more accurate results. The Variance Inflation Factor (VIF) is used to measure multicollinearity by estimating the correlation between independent variables

and assessing how much multicollinearity inflates the variance of a regression coefficient. A VIF value below 2.5 indicates that the independent variables are not significantly correlated, while values between 2.5 and 10 suggest moderate correlation. A VIF greater than 10 signals a high degree of multicollinearity between independent variables.

The bikeshare data for 2020 were tested for multicollinearity over the complete analysis period. The results of the multicollinearity test for the independent variables are shown in Table 3.1. As indicated in the table, the highest VIF value among the independent variables is 1.19, with all VIF values below 2.5. This confirms that there are no significant correlations between the independent variables, meaning they are sufficiently independent of one another for use in the analysis.

**Table 3.1: Multicollinearity Test Results (Variance Inflation Factor)**

| <b>COVID-19 Daily Cases</b> | <b>Weekend Indicator</b> | <b>Temperature</b> | <b>Precipitation</b> |
|-----------------------------|--------------------------|--------------------|----------------------|
| 1.15                        | 1.01                     | 1.19               | 1.04                 |

Table 3.2 provides an overview of the variables used in the analysis, including their units of measurement, data sources, and statistical summaries (such as minimum, maximum, mean, and standard deviation). The dependent variable in this analysis is the average daily ridership. The four independent variables include the daily count of COVID-19 cases, the weekend indicator, and two weather-related factors. The weather-related variables consist of daily temperature and daily precipitation (measured in inches).

**Table 3.2: Descriptive Statistics of Variables**

| <b>Variables (Units)</b>     | <b>Min</b> | <b>Max</b> | <b>Mean</b> | <b>Std. Dev</b> | <b>Source</b>                                       |
|------------------------------|------------|------------|-------------|-----------------|---|
| <b>DEPENDENT</b>             |            |            |             |                 |   |
| Bikeshare Trips (count)      | 76         | 1,944      | 969.89      | 363.82          | Houston bikeshare                                   |
| <b>INDEPENDENT</b>           |            |            |             |                 |   |
| COVID-19 Daily Cases (count) | 0          | 2,247      | 367.35      | 336.94          | Harris County and City of Houston COVID-19 data hub |
| Weekend Indicator            | 0          | 1          | 1,298.73    | 414.13          | Houston BCycle                                      |
| Temperature Indicator        | 0          | 1          | 79.14       | 7.96            | NOAA  |
| Precipitation (inch)         | 0          | 3.58       | 0.13        | 0.38            | NOAA  |

A weekend indicator of 0 and 1 was used in the model, where 1 represented weekend days and 0 represented weekdays. Additionally, instead of using daily average temperatures as a continuous variable, temperature indicators of 0 and 1 were employed. A value of 1 was assigned to days with average temperatures between 55°F and 85°F, which are considered favorable for cycling in Houston. For days with average temperatures below 55°F or above 85°F - conditions deemed too cold or too hot for cycling - the indicator was set to 0.

### 3.4 Model Selection

In this study, the R programming language was used to conduct statistical analyses and modeling on Houston bikeshare ridership. Since bikeshare ridership represents count data, different methods are required than those used for conventional linear regression models, which assume a normal distribution of the data. One of the most common methods for modeling count data is the Poisson regression model, which assumes a Poisson distribution for the dependent variable,  $y$ . However, a limitation of the Poisson model is that it assumes the variance of the data is equal to the mean.

To account for overdispersion - when the variance exceeds the mean - Negative Binomial regression is typically used, as it allows for greater variance than the mean. Count data often exhibit overdispersion, making the Negative Binomial regression model a more appropriate choice. To determine the best model for this data, a likelihood ratio test was performed to compare the effectiveness of the Poisson and Negative Binomial regression models. The likelihood ratio test yielded a p-value of less than 5%, leading to the rejection of the null hypothesis and confirming that the Negative Binomial model was significantly better suited for the data than the Poisson model.

Additionally, the Akaike Information Criterion (AIC) for the Negative Binomial regression model was lower than that for the Poisson regression model, and the Log-likelihood value was higher, further supporting the selection of the Negative Binomial model as the appropriate statistical method.

### 3.5 Negative Binomial Regression Model

One of the key limitations of the Poisson model is its inherent assumption that the variance of the dependent variable ( $y_i$ ) is equal to its mean. This restrictive property often does not hold in practice, as overdispersion is common in real-world data. Overdispersion occurs when the variance of the data exceeds the mean, which is often the case with count data like average daily ridership. When overdispersion is present, the Poisson regression model becomes inadequate.

To address this issue, the Negative Binomial regression model is used, as it relaxes the overdispersion constraint by allowing the variance to exceed the mean. This approach makes the Negative Binomial model more suitable for count data with overdispersion, such as bikeshare ridership. The derivation of the Negative Binomial regression model begins with the Poisson model, which is defined by the following equation (Chang, 2005):

$$P(n_i) = \frac{\exp(-\lambda_i) \lambda_i^{y_i}}{y_i!} \quad (1)$$

where  $P(n_i)$  represents the probability that bikeshare  $i$  experiences an average daily ridership of  $n_i$ , and  $\lambda_i$  is the Poisson parameter, which corresponds to the expected average daily ridership for

bikeshare  $i$ . In applying the Poisson model, the average daily ridership is assumed to be a function of explanatory variables, such that

$$\lambda_i = \exp(x_i \beta) \quad (2)$$

where  $x_i$  is a vector of explanatory variables, and  $\beta$  is a vector of estimated coefficients, which can be estimated using the maximum likelihood method with the likelihood function being

$$L(\beta) = \prod_i \frac{\exp[-\exp(\beta x_i)] [\exp(\beta x_i)]^{n_i}}{n_i!} \quad (3)$$

To address the issue of overdispersion, Negative Binomial regression can be employed, which relaxes the assumption that the mean of accident frequencies equals the variance. This is achieved by introducing an error term to the average daily ridership ( $\lambda_i$ ), modifying Equation (2) as follows:

$$\lambda_i = \exp(\beta x_i + \varepsilon_i) \quad (4)$$

where  $\exp(\varepsilon_i)$  represents a gamma-distributed error term with a mean of one and a variance of  $1/\theta$ . This adjustment yields the conditional probability.

$$p(n_i | \varepsilon) = \frac{\exp[-\lambda_i \exp(\varepsilon_i)] [\lambda_i \exp(\varepsilon_i)]^{n_i}}{n_i!} \quad (5)$$

Integrating  $\varepsilon$  out of this expression results in the unconditional distribution of  $n_i$ . This leads to the formulation of the Negative Binomial distribution, which is given by:

$$P(n_i) = \frac{\Gamma(\theta + n_i)}{[\Gamma(\theta)] n_i!} u_i^\theta (1 - u_i)^{n_i} \quad (6)$$

where  $u_i = \theta / (\theta + \lambda_i)$  and  $\theta = 1/\alpha$ , with  $\Gamma$  representing the gamma function. The parameters  $\beta$  and  $\alpha$  of the Negative Binomial regression model can be estimated using the following maximum likelihood function:

$$L(\lambda_i) = \prod_{i=1}^N \frac{\Gamma(\theta + n_i)}{[\Gamma(\theta) n_i!]} \left[ \frac{\theta}{\theta + \lambda_i} \right]^\theta \left[ \frac{\lambda_i}{\theta + \lambda_i} \right]^{n_i} \quad (7)$$

Marginal effects and Incidence Rate Ratios (IRRs) are key output measures in Negative Binomial regression models, providing insights into the relationship between independent variables and count data. These measures help in drawing conclusions and making predictions about the influence of predictor variables on the count outcome. The marginal effect represents the change in the expected count outcome resulting from a one-unit change in an independent variable. It is calculated by taking the derivative of the expected count with respect to the predictor variable. The Incidence Rate Ratio (IRR), on the other hand, reflects the ratio of the expected count rate for one level of a predictor variable relative to another level. It is calculated by taking the exponential of the estimated coefficient for the predictor variable. Both measures are essential for analyzing and interpreting the effects of predictor variables in Negative Binomial regression models, providing a clear understanding of how changes in predictors affect the count outcome.

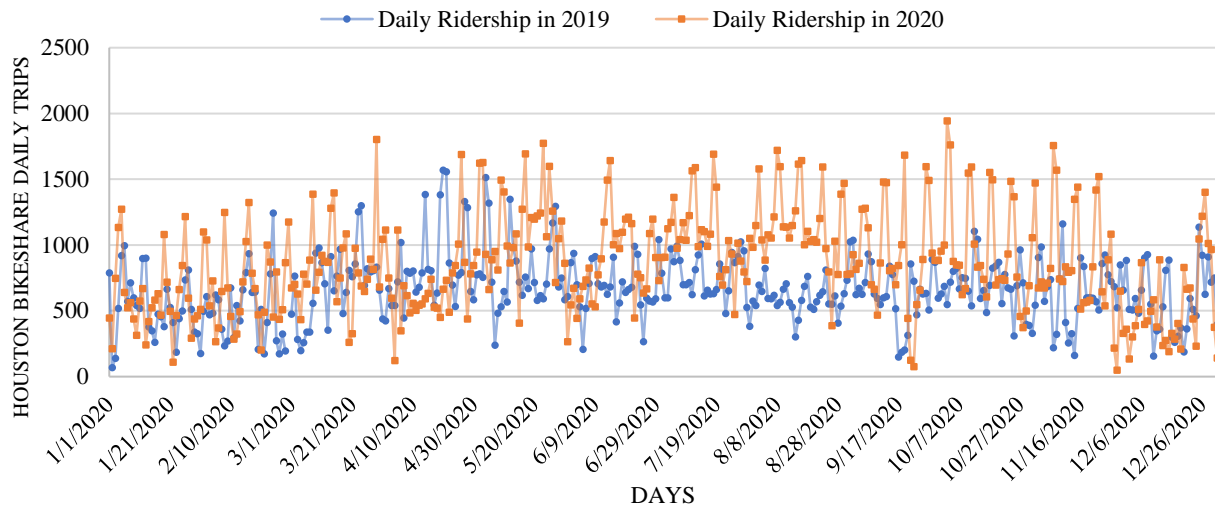
# Chapter 4. Analysis Results

## 4.1 Introduction

This chapter begins by presenting the findings from the descriptive analysis, followed by the results of the Negative Binomial regression model. The descriptive analysis includes figures that summarize the data, along with a discussion of the observed patterns, trends, and relationships between COVID-19 positive cases, Houston bikeshare ridership, temperature, and precipitation. Subsequently, the chapter presents and interprets the results of the Negative Binomial regression model.

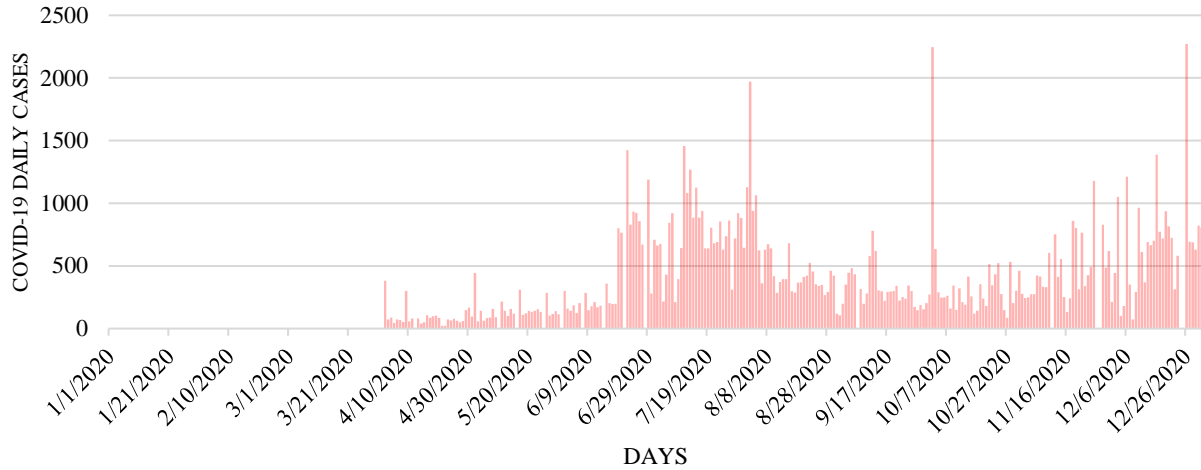
## 4.2 Descriptive Analysis

The Houston bikeshare data reveals a significant surge in the total number of trips taken in 2020, with a 30.6% increase compared to the previous year, resulting in 275,305 trips, as illustrated in Figure 4.1.



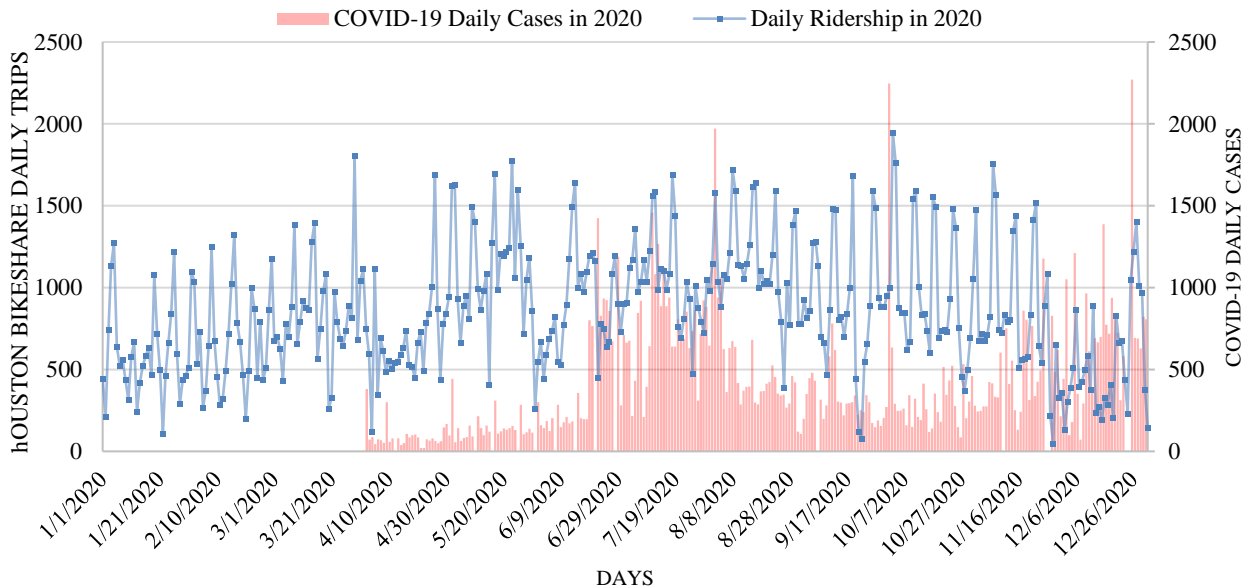
**Figure 4.1: Daily Ridership of the Houston Bikeshare Program, 2020**

In 2020, the city of Houston reported a total of 111,335 COVID-19 cases. Figure 4.2 displays the daily COVID-19 cases recorded in the city throughout the year. The graph shows an upward trend in cases from mid-June to the end of July, with most daily cases exceeding 500. From August to mid-October, there was a decrease in cases, followed by a second surge that continued until the end of the year. The highest number of cases reported on a single day was 2,271, recorded on December 26, 2020. Notably, there were 12 days in 2020 when zero cases were reported. These findings indicate that the COVID-19 pandemic had a profound impact on Houston in 2020, with multiple waves of infections occurring throughout the year.



**Figure 4.2: Daily COVID-19 Case Counts in Houston, 2020**

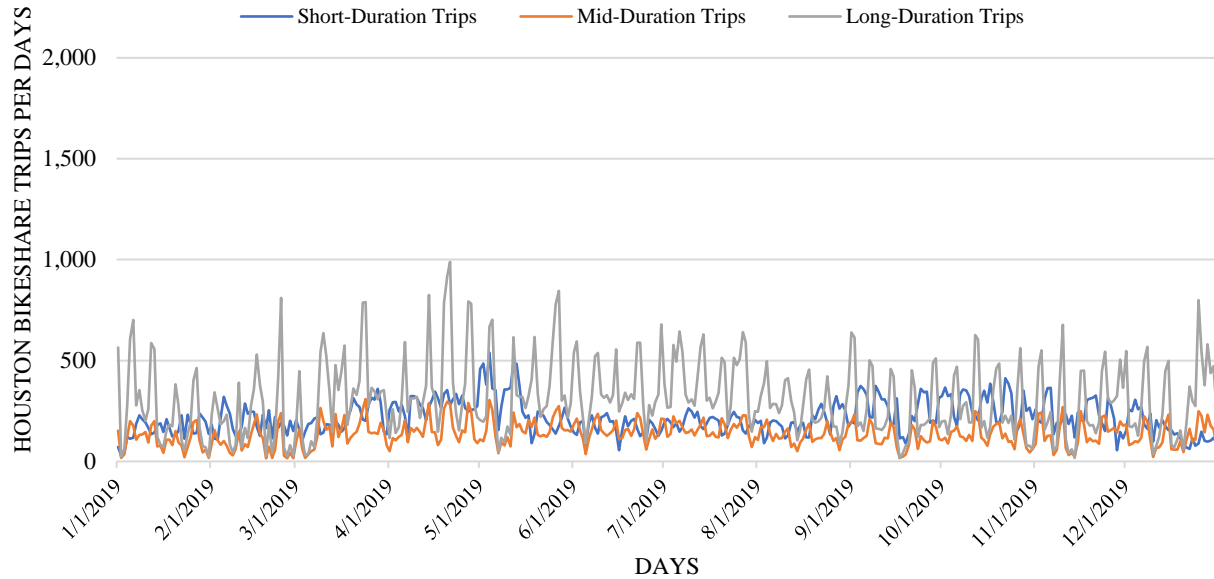
Despite the challenges posed by the COVID-19 pandemic in 2020, Figure 4.3 demonstrates a consistent upward trend in the number of trips taken using the Houston bikeshare program throughout the year. However, there was a noticeable decrease in ridership during mid-June, coinciding with an increase in daily COVID-19 cases. The data also suggests that, generally, a rise in COVID-19 cases was associated with a decline in ridership, with the exception of early and late October, when increases in daily COVID-19 cases corresponded with a rise in ridership. Overall, these findings suggest that the Houston bikeshare program has been effective in promoting sustainable transportation options in the city, even during a year marked by a global health crisis.



**Figure 4.3: Daily Houston Bikeshare Trips and COVID-19 Case Counts in 2020**

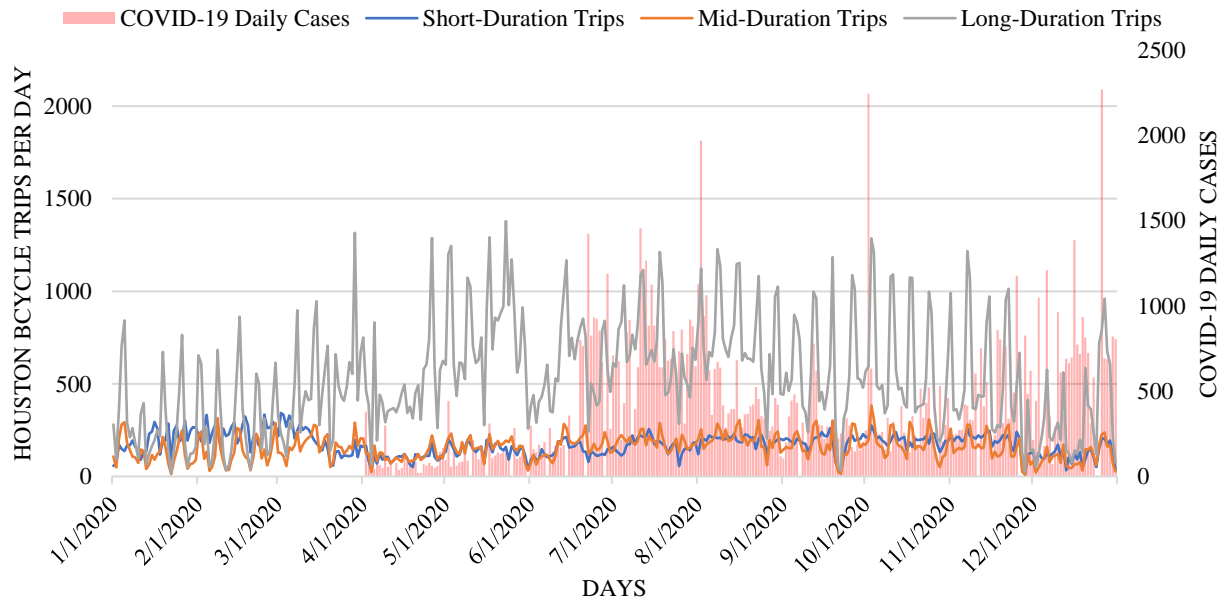
This study also examined how the COVID-19 pandemic influenced the trip durations of Houston bikeshare users, focusing on three categories: short-, mid-, and long-duration trips, as shown in Figure 4.4. Short-duration trips were defined as those lasting less than 15 minutes, mid-

duration trips ranged from 15 to 30 minutes, and long-duration trips exceeded 30 minutes. The findings revealed that in 2019, long-duration trips were more prevalent than both short- and mid-duration trips. Additionally, short-duration trips were more common than mid-duration trips but less frequent than long-duration trips, making mid-duration trips the least prevalent of the three categories.



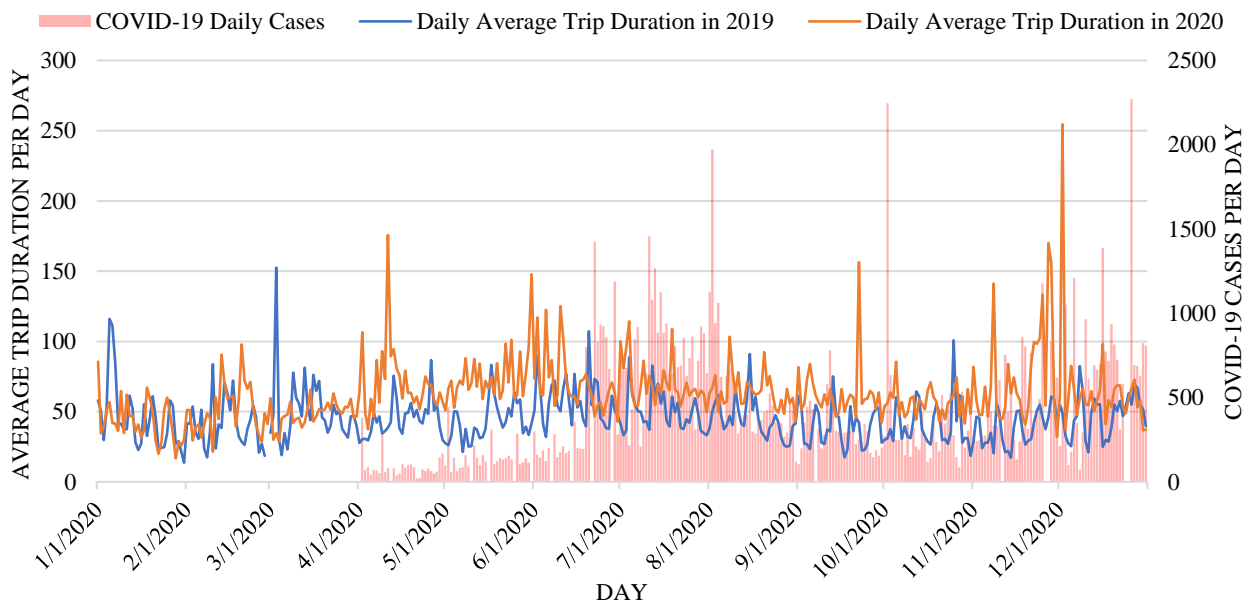
**Figure 4.4: Houston Bikeshare Ridership by Trip Duration Categories in 2019**

Figure 4.5 illustrates a significant increase in the number of long-duration trips in 2020 compared to mid- and short-duration trips. Additionally, Figure 5 highlights the substantial impact of the COVID-19 pandemic on Houston bikeshare trip durations, as evidenced by the contrasting patterns between 2019 and 2020. In particular, long-duration trips were far more prevalent in 2020 than in 2019, while short- and mid-duration trips were less frequent in 2020 compared to the previous year.



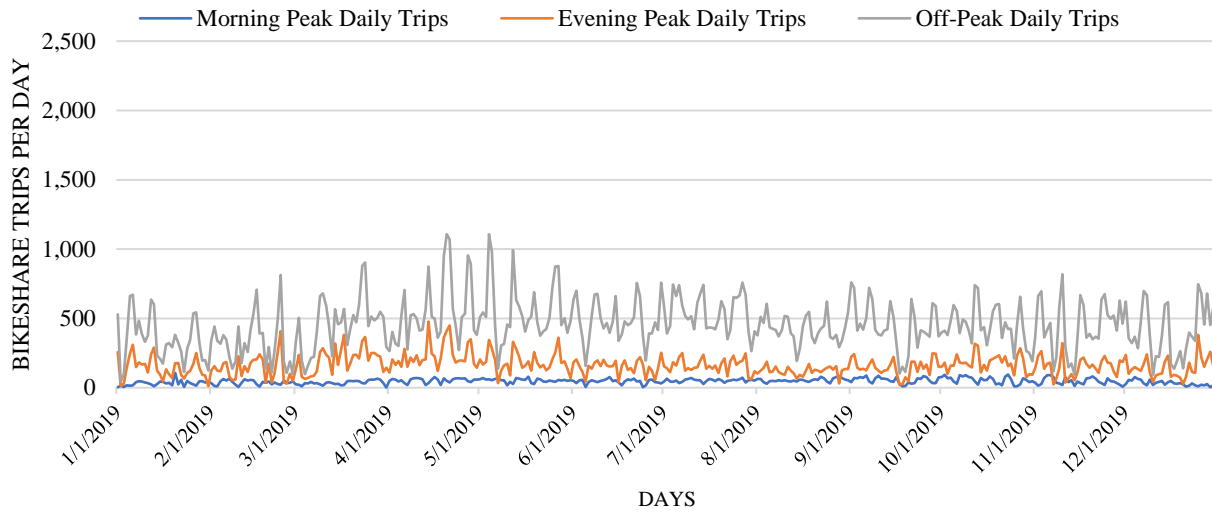
**Figure 4.5: Houston Bikeshare Ridership by Trip Duration Categories in 2020 and Daily COVID-19 Case Counts**

Figure 4.6 shows that in early 2020, before the onset of the COVID-19 pandemic, the daily average trip durations were fairly similar to those during the corresponding period in 2019. However, once the pandemic began, the daily average trip durations in 2020 increased compared to those in 2019. These findings indicate that the pandemic significantly influenced trip duration patterns among Houston bikeshare riders, highlighting the importance for bikeshare operators to remain adaptable and responsive to shifts in ridership patterns due to external factors.



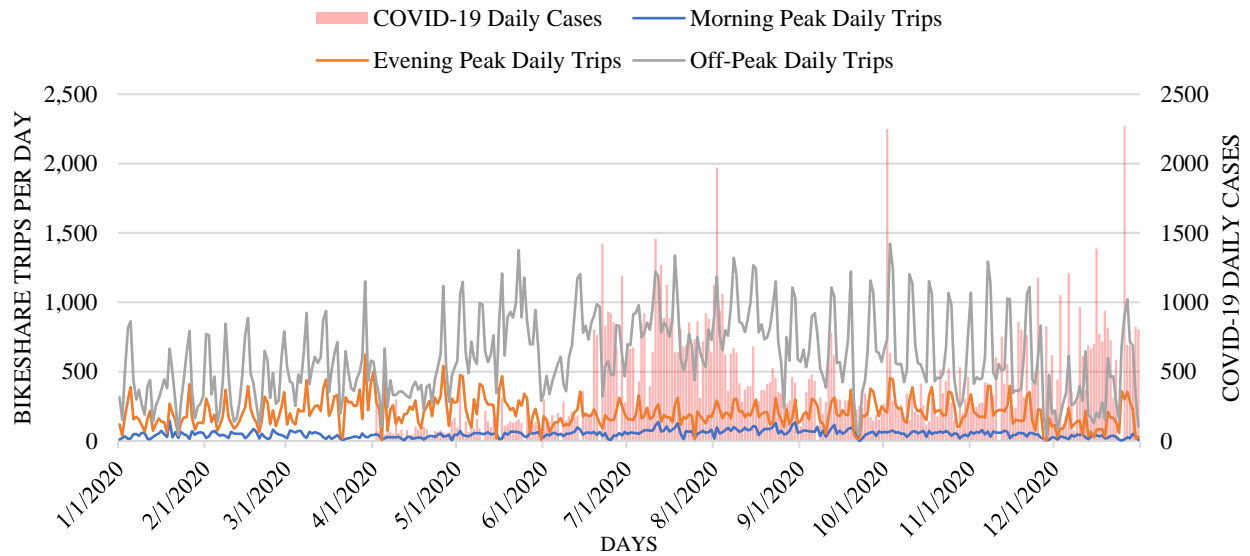
**Figure 4.6: Daily Average Trip Durations and COVID-19 Case Counts for Houston Bikeshare in 2020**

Additionally, the impact of the COVID-19 pandemic on trip occurrences at different times of the day was examined. Using historical traffic data and Houston TranStar traffic maps, off-peak and peak hours were identified for the Houston bikeshare service area. Morning peak hours were defined as 6:30 AM to 9:30 AM, evening peak hours as 4:00 PM to 7:00 PM, with all other hours classified as off-peak. Figure 4.7 shows that, prior to the pandemic in 2019, the majority of trips occurred during off-peak periods, followed by evening peak hours, with morning peak hours having the fewest trips.



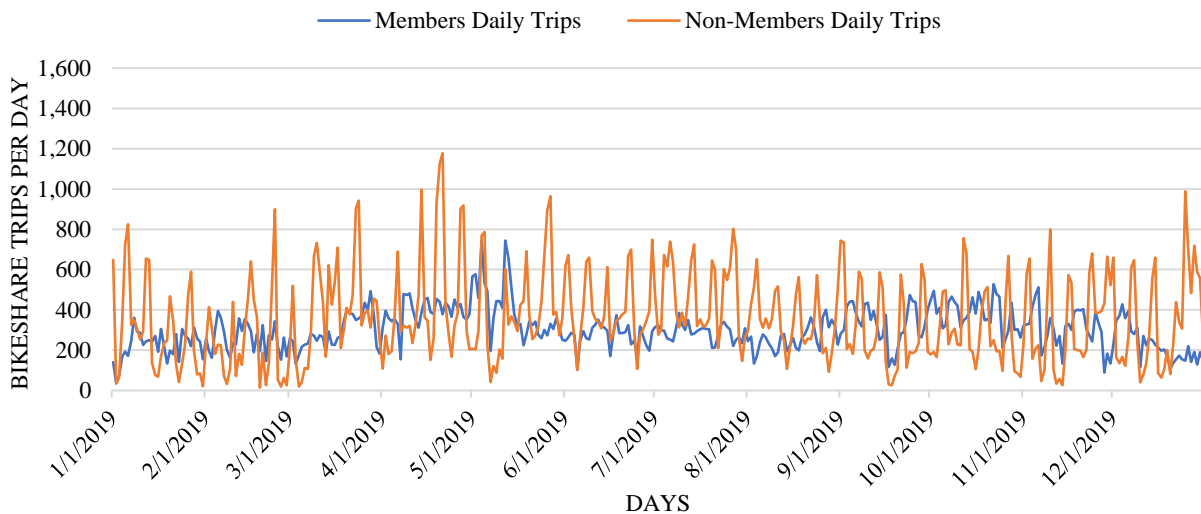
**Figure 4.7: Houston Bikeshare Daily Trips During Peak and Off-Peak Hours in 2019**

Figure 4.8 shows that the COVID-19 pandemic in 2020 led to a significant increase in off-peak trips, with comparatively smaller increases in trips during morning and evening peak periods compared to 2019. The graph illustrates an overall shift in travel patterns during the pandemic, with more individuals opting to travel during off-peak hours rather than during the traditional morning and evening peak periods.



**Figure 4.8: Houston Bikeshare Daily Trips During Peak and Off-Peak Hours and COVID-19 Case Counts in 2020**

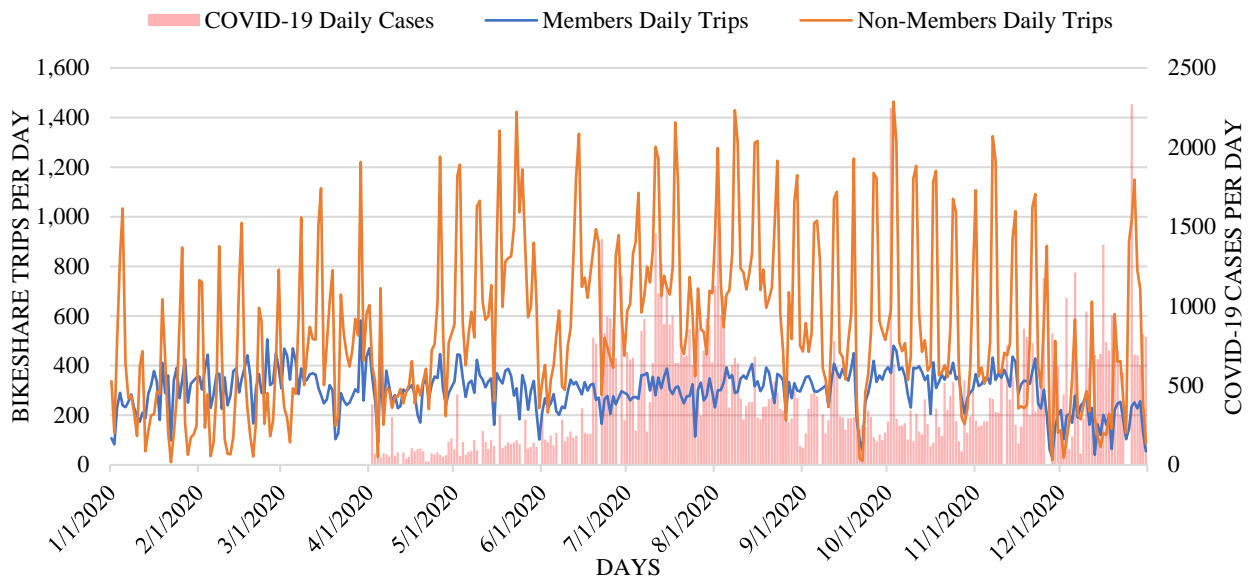
Additionally, the impact of the COVID-19 pandemic on the ridership of Houston bikeshare members and non-members was analyzed using data from 2019 and 2020. Figure 4.9 presents the ridership data for members and non-members in 2019, showing that the total number of trips made by members and non-members were 110,119 and 130,682, respectively. The analysis revealed that, on average, non-members made more trips per day (358) compared to members (302), with most daily trips ranging between 150 and 750. This suggests that non-members had a higher level of ridership than members in the pre-pandemic period throughout 2019.



**Figure 4.9: Daily Trips by Members and Non-Members of Houston Bikeshare in 2019**

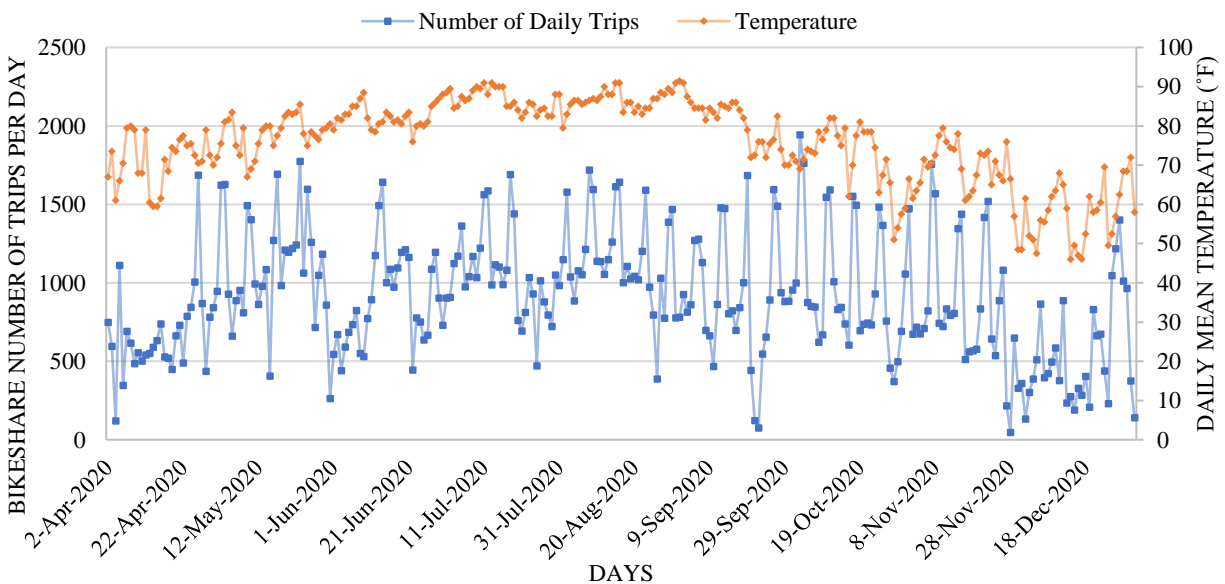
Based on the findings from Figure 4.10, the number of trips made by members during the COVID-19 pandemic in 2020 remained consistent with the pre-pandemic levels of 2019.

However, there was a significant 55.7% increase in the number of trips made by non-members, rising from 130,682 in 2019 to 203,467 in 2020. On average, non-members made 556 trips per day in 2020, indicating a substantial increase in their ridership during the COVID-19 pandemic.

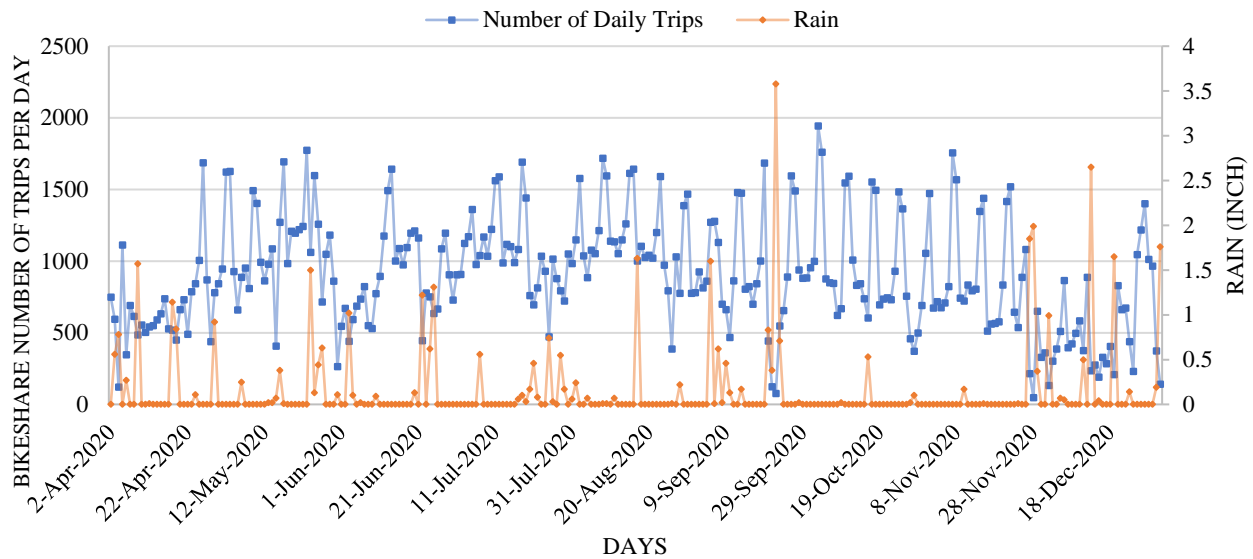


**Figure 4.10: Daily Trips by Members and Non-Members of Houston Bikeshare and COVID-19 Case Counts in 2020**

Finally, the impact of average temperature and precipitation on Houston bikeshare ridership in 2020 was analyzed. The graph in Figure 4.11(a) indicates that there is no clear relationship between the number of bikeshare riders and temperature. However, Figure 4.11(b) reveals a significant decrease in bikeshare ridership on rainy days.



**(b) Ridership and Temperature**



(b) Ridership and Rainfall

Figure 4.11: Houston Bikeshare Daily Ridership in Relation to Temperature (a) and Rainfall (b) in 2020

### 4.3 Negative Binomial Regression Model Results

Table 4.1 presents the coefficients, standard errors, z-values, and p-values for the Negative Binomial regression model. The significance threshold for the independent variables is set at 5%. Asterisk symbols in the last column indicate the significance levels of the independent variables and their impact on the dependent variable, which is the average daily ridership. A single asterisk (\*) denotes a low significance level, while double (\*\*) and triple (\*\*\*) asterisks indicate moderate and high significance levels, respectively.

Table 4.1: Negative Binomial Regression Results

| Independent Variable  | Coefficient | Std. Error | z-value | p-value  |
|-----------------------|-------------|------------|---------|----------|
| COVID-19 Daily Cases  | 0.00013     | 0.00007    | 2.006   | 0.045*   |
| Weekend Indicator     | 0.4583      | 0.046      | 9.991   | 0.000*** |
| Temperature Indicator | -0.05734    | 0.052      | -1.101  | 0.271    |
| Precipitation         | -0.4785     | 0.054      | -8.911  | 0.000*** |

The results of the Negative Binomial regression model indicate that the coefficients for COVID-19 daily cases, the weekend indicator, and precipitation have a significant impact on the dependent variable, as evidenced by their p-values being smaller than 5%. Conversely, the temperature variable has a p-value greater than 5%, suggesting that it does not have a significant

impact and should be excluded from the final model. Table 4.2 summarizes the key findings of the Negative Binomial regression model.

**Table 4.2: Negative Binomial Regression Results Considering Three Independent Variables**

| <b>Independent Variable</b> | <b>Coefficients</b> | <b>Std. Error</b> | <b>z-value</b> | <b>p-value</b> |
|-----------------------------|---------------------|-------------------|----------------|----------------|
| COVID-19 Daily Cases        | 0.00016             | 0.00006           | 2.638          | 0.00834**      |
| Weekend Indicator           | 0.455               | 0.046             | 9.924          | 0.000***       |
| Precipitation               | -0.491              | 0.053             | -9.289         | 0.000***       |

Table 4.3 presents the estimated marginal effects and Incidence Rate Ratios (IRR) for the independent variables included in the final model.

**Table 4.3: Model Results - Estimated Coefficients, Marginal Effects, and Incidence Rate Ratios (IRR)**

| <b>Independent Variable</b> | <b>Coefficients</b> | <b>Marginal Effects</b> | <b>Incident Rate Ratios (IRR)</b> |
|-----------------------------|---------------------|-------------------------|-----------------------------------|
| COVID-19 Daily Cases        | 0.00016             | 0.1596                  | 1.000163                          |
| Weekend Indicator           | 0.455               | 444.913                 | 1.5755                            |
| Precipitation               | -0.491              | -480.838                | 0.6118                            |

Tables 4.2 and 4.3 present the results of the Negative Binomial regression model, which provide insights into the effects of various independent variables on the dependent variable, average daily ridership ( $y$ ). By analyzing the coefficient estimates, standard errors, p-values, marginal effects, and incidence rate ratios for each independent variable, we can better understand their impact on ridership. Detailed explanations for the selected independent variables are provided below.

The results in Table 4.2 indicate a statistically significant positive impact of COVID-19 cases on average daily ridership. Specifically, for each additional COVID-19 case, the average daily ridership is estimated to increase by 0.1596 trips per day, corresponding to a percentage increase of approximately 0.0163%. The weekend indicator has the strongest statistically significant positive impact on average daily ridership, as shown in Table 4.2. Conversely, the results presented in Table 4.1 reveal a relatively high p-value associated with the temperature indicator, suggesting that temperature has no statistically significant impact on average daily ridership. Table 4.2 also suggests that precipitation has the strongest statistically significant negative impact on average daily ridership. Specifically, for each additional inch of rain, the average daily ridership is estimated to decrease by 480.838 trips per day, corresponding to a percentage reduction of about 38.82%.



## **Chapter 5. Summary and Conclusions**

### **5.1 Introduction**

Previous research has explored the influence of various factors on bike-sharing ridership. Some studies relied on surveys to capture user behavior or conducted observations and experiments in specific locations, often lacking a comprehensive understanding of bikeshare activities across the entire system. In contrast, this study employed a Negative Binomial regression model to examine the effects of the COVID-19 pandemic on average daily ridership in Houston's bikeshare system. The study was conducted to address the gap in understanding the full impact of the COVID-19 pandemic on bikeshare usage in Houston.

### **5.2 Summary and Conclusions**

For the analyses, real-world data encompassing the entire population of interest was used, rather than relying on samples. Two types of analyses were conducted: descriptive and regression analysis. The descriptive analysis compared bikeshare usage immediately before the outbreak of COVID-19 to usage during the pandemic, followed by regression modeling. The descriptive analysis revealed a significant increase in the total number of bike trips taken in Houston in 2020, with a 30.6% rise compared to the previous year. The COVID-19 pandemic significantly impacted the duration and timing of trips, with longer trips becoming more common and mid-duration trips less frequent in 2020. Additionally, the total trip duration increased by 73.52% in 2020. The pandemic also caused a shift in travel patterns, with more people traveling during off-peak hours rather than during the morning and evening peak periods. While the number of trips by members remained constant during the pandemic, there was a significant increase in non-member trips in 2020. There was no observed correlation between bikeshare ridership and temperature, but rainy days led to a significant decrease in ridership. These findings suggest that the Houston bikeshare program has effectively promoted sustainable transportation options in the city despite the challenges posed by the pandemic, and they underscore the importance of flexibility in response to changing ridership patterns due to external factors.

For regression modeling, likelihood tests were conducted to compare the Negative Binomial and Poisson regression models, confirming that the Negative Binomial regression model was appropriate for the Houston bikeshare data. The regression analysis results indicated that each additional positive COVID-19 case in Houston would result in an average increase of 0.1596 trips per day. Furthermore, during weekends, the average daily ridership increased by 444.9 trips. Temperature had no significant impact on daily trip counts, while precipitation had a significant negative impact. Specifically, each inch of precipitation was associated with a decrease of 480.838 trips per day, indicating that rainfall had a substantial effect on ridership.

City planning agencies are interested in understanding future cycling patterns in the event of another pandemic similar to COVID-19, and bikeshare operators seek to forecast system demand under such conditions. It is crucial to quantify how bikeshare ridership will change in response to each additional positive COVID-19 case. The model proposed in this study can measure the impacts of the COVID-19 pandemic by capturing system-wide bike ridership, and it can be used to forecast demand for the Houston bikeshare system during a health crisis. The

factors considered in this model include the COVID-19 pandemic, weekday versus weekend, temperature, and precipitation.

### **5.3 Directions for Future Research**

This study focused on the impact of COVID-19 "positive cases" on bikeshare ridership without accounting for state and government policies and restrictions related to the pandemic. For example, during 2020, many employees were working from home. Additionally, the rollout of COVID-19 vaccinations reduced hospitalizations and deaths, leading to a gradual return to workplaces in 2021 and 2022, even though the number of COVID-19 positive cases had not significantly decreased. Therefore, future studies should consider the influence of such policies on ridership trends.

Future research could explore additional variables that might impact bikeshare ridership, such as factors related to bike infrastructure. Additionally, investigating the impact of COVID-19 on bikeshare stations located near major activity centers, such as universities, parks, and hospitals, would be valuable. Future studies should also focus on long-duration trips, which increased during the pandemic. Moreover, utilizing data from 2021 could help identify potential trends, providing a better comparison of bikeshare usage before, during, and after the pandemic.



## References

- Air Alliance Houston, LINK Houston, & Texas Southern University. (n.d.). COVID and public transit in the Houston region. Houston.
- Albuquerque, V., Andrade, F., Ferreira, J., Dias, M., & Bacao, F. (2018). Bike-sharing mobility patterns: A data-driven analysis for the city of Lisbon. *EAI Endorsed Transactions on Smart Cities*, 169580. <https://doi.org/10.4108/eai.4-5-2021.169580>
- American Public Transportation Association. (2021). The impact of the COVID-19 pandemic on public transit funding needs in the U.S.
- Berezvai, Z. (2022). Short- and long-term effects of COVID-19 on bicycle sharing usage. *Transportation Research Interdisciplinary Perspectives*, 15, 100674. <https://doi.org/10.1016/j.trip.2022.100674>
- Bustamante, X., Federo, R., & Fernández-i-Marín, X. (2022). Riding the wave: Predicting the use of the bike-sharing system in Barcelona before and during COVID-19. *Sustainable Cities and Society*, 83, 103929. <https://doi.org/10.1016/j.scs.2022.103929>
- Chang, L.-Y. (2005). Analysis of freeway accident frequencies: Negative binomial regression versus artificial neural network. *Safety Science*, 43(8), 541–557. <https://doi.org/10.1016/j.ssci.2005.04.004>
- Jiao, J., Lee, H. K., & Choi, S. J. (2022). Impacts of COVID-19 on bike-sharing usages in Seoul, South Korea. *Cities*, 130, 103849. <https://doi.org/10.1016/j.cities.2022.103849>
- Kim, K. (2021). Impact of COVID-19 on Usage Patterns of a Bike-Sharing System: Case Study of Seoul. *Journal of Transportation Engineering, Part A: Systems*, 147(10), 05021006. <https://doi.org/10.1061/JTEPBS.0000591>
- Li, H., Zhang, Y., Zhu, M., & Ren, G. (2021). Impacts of COVID-19 on the usage of public bicycle share in London. *Transportation Research Part A: Policy and Practice*, 150, 140–155. <https://doi.org/10.1016/j.tra.2021.06.010>
- Liu, L., Miller, H. J., & Scheff, J. (2020). The impacts of COVID-19 pandemic on public transit demand in the United States. *Plos one*, 15(11), e0242476.
- Marich, M. (2016, October 12). BCYCLE INTRODUCES BIKE SHARE INDUSTRY'S FIRST FULLY INTEGRATED ECOSYSTEM. BCycle. <https://www.bcycle.com/news/2016/10/12/bcycle-introduces-bike-share-industry-s-first-fully-integrated-ecosystem>
- Najarro, I. (2018, November 13). Houston BCycle expands into Texas Southern University. *Houston Chronicle*. <https://www.chron.com/local/article/Houston-Bcycle-expands-into-Texas-Southern-13388194.php>

Padmanabhan, V., Penmetsa, P., Li, X., Dhondia, F., Dhondia, S., & Parrish, A. (2021). COVID-19 effects on shared-biking in New York, Boston, and Chicago. *Transportation Research Interdisciplinary Perspectives*, 9, 100282. <https://doi.org/10.1016/j.trip.2020.100282>

Qi, Y., Liu, J., Tao, T., Zhao, Q., Muhammad Wali, M., Li, J., & Azimi, M. (2022). Impacts of COVID-19 on public transit ridership. Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE).

Rozen, S. (2021, October). Report finds need for sustainable, reliable public transit throughout COVID-19 pandemic. *Community Impact Newspaper*. Retrieved from <https://communityimpact.com/houston/bay-area/transportation/2021/10/28/report-finds-need-for-sustainable-reliable-public-transit-throughout-covid-19-pandemic/>

Schmitt, A. (2018, April 26). Pro Tip for Managing Dockless Bike-Share “Clutter”—Give Them Space on the Street. *STREETSBLOG USA*. <https://usa.streetsblog.org/2018/04/26/pro-tip-for-managing-dockless-bike-share-clutter-give-them-space-on-the-street/>

Shaheen, S. A., Chan, N. D., & Micheaux, H. (2015). One-way carsharing’s evolution and operator perspectives from the Americas. *Transportation*, 42(3), 519–536. <https://doi.org/10.1007/s11116-015-9607-0>

Sung, H. (2023). Causal impacts of the COVID-19 pandemic on daily ridership of public bicycle sharing in Seoul. *Sustainable Cities and Society*, 89, 104344. <https://doi.org/10.1016/j.scs.2022.104344>

Teixeira, J. F., & Lopes, M. (2020). The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York’s Citi Bike. *Transportation Research Interdisciplinary Perspectives*, 6, 100166. <https://doi.org/10.1016/j.trip.2020.100166>  
TransLoc. (2021). Transit Value Index.

Vo, T., Barbour, N., Palaio, L., & Maness, M. (2022). Impacts of the COVID-19 Pandemic on Bikeshare Usage by Rider Membership Status Across Selected U.S. Cities. *Transportation Research Record: Journal of the Transportation Research Board*, 036119812211315. <https://doi.org/10.1177/03611981221131542>

Wang, H., & Noland, R. (2021). Changes in the Pattern of Bikeshare Usage due to the COVID-19 Pandemic. *Findings*. <https://doi.org/10.32866/001c.18728>

