JOINT TRANSPORTATION RESEARCH PROGRAM

INDIANA DEPARTMENT OF TRANSPORTATION
AND PURDUE UNIVERSITY

Assessing the Travel Demand and Mobility Impacts of Transformative Transportation Technologies in Indiana

Hao Luo, Ricardo Chahine, Arianna Rambaram,
Elizabeth Theresa Rosenzweig, Konstantina Gkritza, Hua Cai

SPR-4413 • Report Number: FHWA/IN/JTRP-2022/11 • DOI: 10.5703/1288284317374

RECOMMENDED CITATION

Luo, H., Chahine, R., Rambaram, A., Rosenzweig, E. T., Gkritza, K., & Cai, H. (2022). *Assessing the travel demand and mobility impacts of transformative transportation technologies in Indiana* (Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2022/11). West Lafayette, IN: Purdue University. https://doi.org/10.5703/1288284317374

AUTHORS

Hao Luo
Graduate Research Assistant
Environmental and Ecological Engineering
Purdue University

Ricardo Chahine
Arianna Rambaram
Graduate Research Assistants
Lyles School of Civil Engineering
Purdue University

Elizabeth Theresa Rosenzweig
Undergraduate Researcher
Lyles School of Civil Engineering
Purdue University

Konstantina Gkritza, PhD
Professor of Civil Engineering and Agricultural and
Biological Engineering
Lyles School of Civil Engineering
Department of Agricultural & Biological Engineering
Purdue University
(765) 494-4597
nadia@purdue.edu
Corresponding Author

Hua Cai, PhD, PE
Associate Professor of Environmental and Ecological Engineering
School of Industrial Engineering
Purdue University
(765) 494-7701
huacai@purdue.edu
Corresponding Author

JOINT TRANSPORTATION RESEARCH PROGRAM

The Joint Transportation Research Program serves as a vehicle for INDOT collaboration with higher education institutions and industry in Indiana to facilitate innovation that results in continuous improvement in the planning, design, construction, operation, management and economic efficiency of the Indiana transportation infrastructure. https://engineering.purdue.edu/JTRP/index_html

Published reports of the Joint Transportation Research Program are available at http://docs.lib.purdue.edu/jtrp/.

NOTICE

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA/IN/JTRP-2022/11		

4. Title and Subtitle Assessing the Travel Demand and Mobility Impacts of Transformative Transportation Technologies in Indiana	**5. Report Date** April 2022 **6. Performing Organization Code**
7. Author(s) Hao Luo, Ricardo Chahine, Arianna Rambaram, Elizabeth Thereasa Rosenzweig, Konstantina Gkritza, and Hua Cai	**8. Performing Organization Report No.** FHWA/IN/JTRP-2022/11
9. Performing Organization Name and Address Joint Transportation Research Program Hall for Discovery and Learning Research (DLR), Suite 204 207 S. Martin Jischke Drive West Lafayette, IN 47907	**10. Work Unit No.** **11. Contract or Grant No.** SPR-4413
12. Sponsoring Agency Name and Address Indiana Department of Transportation (SPR) State Office Building 100 North Senate Avenue Indianapolis, IN 46204	**13. Type of Report and Period Covered** Final Report **14. Sponsoring Agency Code**

15. Supplementary Notes

Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration.

16. Abstract

The rapid development of transformative transportation technologies, such as bike-sharing, shared e-scooters, and ride-hailing systems, is reshaping the transportation landscape. These transformative transportation technologies have the potential to significantly change travel behavior and travel demand and affect transportation agencies' planning, operations, and decision-making. The objective of this project is to develop a framework and models to quantify the potential travel demand and mobility impacts of transformative transportation technologies in Indiana cities. This project analyzed historical system usage data and conducted survey studies to evaluate the availability and use of transformative transportation technologies in select Indiana cities. The project also proposed a data-driven model to study the relationship between shared micro-mobility and the existing transit system and developed a simulation model to analyze the potential mode choice change under different future development scenarios. Additionally, based on a comprehensive literature review, a list of operations; environmental, health and safety; and accessibility and equity metrics were identified as the Key Performance Indicators to evaluate transformative transportation technologies. Furthermore, as this study was conducted in the midst of the COVID-19 pandemic, the impacts of the pandemic on both traditional and transformative transportation systems were also examined as documented in the literature and stated in our survey.

17. Key Words	18. Distribution Statement
transformative transportation technology, travel demand, bike-sharing, shared e-scooters, ride-hailing, multi-modal transportation, COVID-19 pandemic	No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	98 including appendices	

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

EXECUTIVE SUMMARY

Introduction

The rapid development of transformative transportation technologies, such as bike-sharing, shared e-scooters, and ride-hailing systems, can dramatically change the transportation system and impact transportation agencies' planning, operations, and decision-making. This project evaluated the availability, use, and impact of transformative transportation technologies in Indiana cities using a diverse set of data sources and tools, such as historical trip data, surveys, and simulation models.

Findings

Shared micro-mobility (i.e., bike-sharing and shared e-scooters) and ride-hailing services are the dominant transformative transportation technologies currently available in Indiana cities. In general, shared e-scooter systems are much larger than bike-sharing systems and have higher usage rates. Ride-hailing is more prevalent than both bike-sharing and shared e-scooters.

Transformative transportation technologies have not significantly affected car usage in Indiana cities but decreased transit use. Shared micro-mobility is replacing public transit more than complementing it. Very few users have been using shared micro-mobility to serve the first-/last-mile connections to access bus service. The operation and regulation of shared micro-mobility systems need to be carefully designed to improve urban mobility. The continuous development of transformative transportation technologies, in terms of improved availability and reduced price, is anticipated to impact private vehicle use and overall VMT (vehicle miles traveled). In the short term, it is unlikely that car ownership will decrease due to these transformative transportation technologies because they cannot fully meet the diversity in travel demands.

This study also provided a summary of literature on the impact that COVID-19 had on traditional and transformative transportation system usage. The beginning stage of the pandemic resulted in a decrease in private vehicle and transit use and an increase in walking and cycling nationwide. As of May 2021, trips to residences, grocery stores, and recreational venues have almost achieved pre-pandemic levels, while trips to workplaces and transit stations are still significantly less popular. Survey results from the Greater Lafayette and Indianapolis suggest that both bike-sharing and shared e-scooters were used similarly during COVID-19. Furthermore, insights from the Indianapolis survey show a notable change in travel habits caused by COVID-19.

Implementation

The following recommendations are derived from the findings of this project.

- It is necessary to dynamically monitor and assess transformative transportation system performances to guide policy and investment decisions. Timely information about system usage is needed to support decision-making for regulation and infrastructure development. However, many Indiana cities still lack requirements for data sharing.
- Better integration of transformative systems with traditional transportation systems can enable multimodal trips and improve urban mobility and transportation sustainability; however, this will require integrated trip planning, payment, and fleet management.
- The results from the future adoption simulation can help Indiana MPOs adjust the travel demand model and account for the impact of transformative transportation technologies. For other locations, the developed modeling framework can be applied to generate city-specific results. Results from this project can also inform future long-range transportation plan updates and provide useful information to the Multimodal Transit Team for their annual state transit reports.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION AND BACKGROUND

1.1 Background and Problem Statement

The transportation landscape has been quickly shifting in recent years because of the transformative transportation technologies. Bike-sharing, shared e-scooters, and ride-hailing systems have been launched in many U.S. cities in recent years, and they are still in rapid growth.

Bike-sharing is becoming an increasingly popular alternative transportation mode in U.S. cities. The year 2017 witnessed 35 million bike-sharing trips in the U.S., a 25% increase since 2016 (NACTO, 2017). Bike-sharing systems provide users with on-demand access to shared bikes for short-term usage. There are two types of bike-sharing systems—station-based systems and dock-less systems. In a station-based system, the users check out a bike at a docking station and then return it to the same or another station after the trip. In a dock-less system, because all the necessary electronic devices are incorporated into the bikes instead of in the docks, the users can locate and unlock a bike with a smartphone application and then park and lock the bike without the restriction of docking stations. Currently, the station-based bike-sharing system is the dominant player in Indiana cities. This study will only focus on the station-based system.

Contrary to bike-sharing, the start and expansion of shared e-scooters are more recent and rapid. The stand-up e-scooter, consisting of an electric motor and a standing deck, is designed for a user to ride for a short distance in urban areas (Hollingsworth et al., 2019). Shared e-scooter companies launch these e-scooter fleets for shared use and allow users to drop off the e-scooters almost anywhere (e.g., on the sidewalk or in designated zones) at the end of a trip for the next user to pick them up (Shaheen & Cohen, 2019). After first being introduced in 2017, shared e-scooter systems have experienced a rapid expansion (NACTO, 2018). In 2018, over 85,000 shared e-scooters have been put into about 100 U.S. cities and served 38.5 million trips (Anderson, 2014; NACTO, 2018).

Another prominent transformative transportation technology mode is ride-hailing (a.k.a. ride-sourcing). This service started with the rise of Uber in 2009 (MOVMI, 2018) and has become an important constituent of the transportation systems in cities around the world. Ride-hailing allows customers to request a ride (like a traditional taxi) using a specific mobile app. Additionally, the service offers several types of rides with different costs depending on the option (e.g., carpooling, extra legroom, luxurious car, etc.), which provides service for different travel needs such as commuting, recreation, etc. The ride-hailing companies, such as Uber, Lyft, Didi, Grab, and Ola, are in rapid growth around the world (Ke et al., 2020). In New York City, ride-sourcing service is now serving over 700 thousand trips per day, almost three times that of taxi trips, and the demand is still increasing (NYC Taxi & Limousine Commission, 2020).

The rapid development of different transformative transportation technologies can potentially change the transportation system dramatically and impact transportation agencies' planning, operations, and decision-making. Existing research has shown that these transformative transportation technologies are impacting vehicle ownership and usage and changing travel demands (Clewlow & Mishra, 2017). However, the impacts of different transformative transportation systems are different to different cities, because of the various pricing plans and operations, different local travel demands, and diverse infrastructure density and availability. For example, while about 30% of the bike-sharing users in Washington, D.C. reported lower use of rail, 13% of Twin Cities bike-sharing users reported increased rail use (Shaheen et al., 2013). Another study conducted by Shaheen et al. (2014) collected survey data from five cities across the United States, Canada, and Mexico. The results show that bike-sharing was responsible for bus usage reduction in four of the five cities. Among the main reasons why respondents switched modes were the lower cost and faster trip that bike-sharing offered compared with public transit. A Chicago shared e-scooter study by Smith and Schwieterman (2018) showed that, for short distance trips, e-scooters can compete with private vehicles especially in a parking constrained environment. For ride-hailing systems, a study by Clewlow and Mishra (2017) deployed travel and residential surveys across several big U.S. cities to assess the impact of ride-hailing on the transportation network. They found that the use of ride-hailing may have caused transit use to decrease by 6% in the major cities. The study argues that new ride-hailing users were mainly attracted away from transit, but the service was also used in some cases to complement the bus. Another survey study by Rayle et al. (2014) conducted in San Francisco showed that ride-hailing services may be replacing a proportion of private vehicles trips. The surveys and models developed to study the impacts of these transformative transportation technologies are also designed for specific case studies of different cities, which limit the transferability of the conclusions to other cities. In addition, existing research focused on large cities, such as New York City, Washington, D.C., and Chicago, with very little attention being paid to smaller and medium-sized urban areas. Therefore, the impact that these transformative transportation technologies can have in cities in Indiana is unclear.

Furthermore, new performance indicators are needed to evaluate these transformative transportation technologies. Because of the transformative transportation concept introduced by the transformative transportation technologies, the existing performance indicators (e.g., household vehicle ownership, vehicle-miles-traveled (VMT)) could not fully measure the efficiency and effectiveness of the transformative systems. The public space and infrastructure (e.g., curb space, sidewalks) are also used differently. Additionally, the existing performance indicators tend to focus on measuring the operational efficiency of each transportation mode in isolation. Some of the transformative transportation technologies may serve the first/last-mile leg in a multimodal transportation trip and help enable and improve public transit use. New mobility key performance indicators (KPIs) considering the "complete trip" concept based on trip chains are needed.

During the process of this project, the COVID-19 pandemic has had a substantial impact on all aspects of human life, including travel activity and transportation systems. From stay-at-home orders to social distancing protocols, these disruptions in life and work patterns may significantly affect human travel and use of both traditional transportation systems and transformative technologies during the pandemic. It is also evident that the pandemic will have lasting effects on transportation services and users' behaviors. Therefore, understanding the potential changes in system usage due to COVID-19 is essential to support policy making on transformative technologies under future pandemic situation and is added to the scope of this project.

In summary, to better understand the impact of transformative transportation technologies and be prepared for the upcoming changes, key questions that are relevant to INDOT's decision-making include the following.

1. What are the appropriate key performance indicators (KPIs) to measure the regional mobility impacts of transformative transportation technologies?
2. What are the current usage patterns of transformative technologies in Indiana cities?
3. How has COVID-19 impacted travel demand and transformative system usage?
4. Are the transformative technologies substituting or complementing the existing modes (e.g., private vehicle, public transportation, biking)?
5. How will different transformative transportation system development scenarios impact vehicle ownership and vehicle use (i.e., vehicle-miles-traveled)?

1.2 Scope of This Study

The objective of this project is to develop a framework and models to quantify the potential travel demand and mobility impacts of transformative transportation technologies in Indiana. This project includes four major research tasks.

1.2.1 Task 1: Analyze the Current Trends of Transformative Transportation Technologies in Select Case Study Cities in Indiana

This task aims to evaluate the transformative transportation technology options that are currently available in Indiana and how these technologies have currently been used. Different cities in Indiana have different transformative transportation technologies that are currently available, with Indianapolis offering more options. We first evaluated the status of available options in different Indiana cities and then selected case study cities (Indianapolis, Greater Lafayette, and Bloomington) for more detailed quantitative analysis. Due to the discontinuity and data unavailability of many systems (e.g., Blue Indy car sharing system in Indianapolis, bike-sharing system in Bloomington), this project focused on ride-hailing, bike-sharing, and shared e-scooter systems in the case studies. We took a data-driven approach, examining historical system usage data, and complemented that data with travel surveys as needed. As some of these technologies are relatively new in Indiana, we also leveraged information from other cities on how adoption and usage have changed over time.

1.2.2 Task 2: Develop Key Performance Indicators (KPIs)

In this task, we proposed a suite of KPIs to evaluate regional economic and mobility impacts of these transformative transportation technologies. The KPIs measure the changes brought by the transformative transportation technologies in the context of the existing transportation system and city infrastructure from various aspects (e.g., cost, equity, accessibility, utilization). We not only measured the system efficiency of each technology, but also considered its relationship to other transportation modes in a multimodal system. We also considered the unique issues that have been brought about by these transformative transportation technologies (e.g., the increased use of curb and sidewalk space, rebalancing using automobiles, and safety).

1.2.3 Task 3: Adoption and Use Simulation Using Agent-Based Models

Based on the collected information and proposed KPIs, we built an agent-based model (ABM) to simulate the adoption, use, and travel behavior change at the household level for the case study city to analyze the potential changes. ABM is a bottom-up modeling approach that has been used in many fields, including transportation (Heath et al., 2009). It has the advantages of considering transportation networks, heterogeneous individual demands and preferences, and complex system interactions in the model and has been used increasingly to study shared mobility systems (Fagnant & Kockelman, 2015; Lokhandwala & Cai, 2018; Shaheen, 2013). The agents in this study are the households (including household members and household-owned vehicles), public transit, and vehicles provided by the transformative transportation technologies (e.g., shared vehicles, bikes, and e-scooters). We simulated the trip for each household and evaluated the time and monetary costs of using different transportation modes to serve the travel demands. The mode choice decisions are modeled using information collected from Task 1 and utility functions developed from a travel survey of the case study city. At both household level and aggregated (city) level, we evaluated the potential changes in VMT, traffic mix, vehicle ownership, mode substitution, and the proposed KPIs across different technology and policy scenarios.

1.2.4 Task 4: Review Literature on Analyzing the Impact of COVID-19 on System Usage

Because this study is conducted during the pandemic, this task aims to provide context about how transportation systems have fared in the beginning, middle, and final stages of the pandemic by reviewing a cluster of COVID-19 related literature.

1.3 Study Benefits and Deliverables

This study generated a suite of modeling and analysis tools and insights that can support INDOT to understand and plan for the potential transportation system changes due to transformative transportation technologies that have emerged in Indiana. The results of this study can help INDOT and Indiana Metropolitan Planning Organizations (MPOs) in the study areas to anticipate the demand for these transformative transportation options and plan accordingly. In specific, the quantification of the impacts associated with the transformative transportation technologies can help INDOT plan accordingly for existing and forthcoming funding needs for operations and infrastructure maintenance. A better understanding of the use and impacts of these transformative transportation options in Indiana can facilitate the incorporation of these transformative transportation technologies into the Transportation Planning Process and the Long-Range Transportation Plan (LRTP). Lastly, developing performance measures/KPIs that can capture the regional mobility impacts of the transformative transportation alternatives can assist INDOT to optimize transportation system performance by considering alternative investment choices to include these innovative technologies.

The following list outlines the main deliverables of this project.

1. A summary of current and emergent trends in the use of transformative technologies on travel demand and mobility in Indiana.
2. A suite of KPIs to evaluate regional economic and mobility impacts of these transformative transportation technologies.
3. A summary of literature that investigated the impact of COVID-19 on transformative technology system usage.
4. Models that evaluate the impact of transformative transportation technologies on travel demand and mobility for different study areas and under different technology and policy scenarios.

1.4 Structure of the Report

The rest of the report is structured as follows. We first summarize the KPIs for traditional transportation modes and then discuss the suitable KPIs for transformative transportation technologies from different perspectives (Chapter 2). Chapter 3 analyzes the system usage patterns of existing transformative transportation technologies in each of the three case study cities, based on historical data. KPIs proposed in Chapter 2 were adopted to evaluate system efficiency. Chapter 4 is a literature review that summarizes existing studies about the COVID-19 impacts on transportation systems. Survey design and results in Indianapolis and Greater Lafayette Area are introduced in Chapter 5 to understand the travel behavior changes of transformative transportation technologies and fill the knowledge gaps of usage patterns in Chapter 3. To quantify the impacts of transformative transportation technologies on transit system, we proposed a data-driven framework in Chapter 6 to investigate the competing and complementary relationship between transformative transportation technologies and existing transit systems and applied the framework to analyze the shared e-scooter system in Indianapolis as a case study. In addition to affecting transit, transformative technologies may also change vehicle usage and ownership. Chapter 7 introduces the agent-based Integrated Traditional and Transformative Transportation System Use Model that is built to simulate the VMT and car ownership change due to the adoption of transformative transportation technologies and discusses results under different development scenarios. Chapter 8 summarizes the key findings and conclusions and discusses the implementation plan.

2. KEY PERFORMANCE INDICATORS

2.1 Chapter Overview

Establishing targets, or performance measures, for systems has proven to be conducive in assessing the success of such systems. Transportation systems and infrastructure are not different. Transportation agencies often derive their own performance measures for the services that they operate to ensure those services reaching the goals desired by the agency. For instance, a transit system's inability to achieve a performance measure may indicate that the service is being underutilized, operating in a non-optimal service area, or performing inefficiently in some other way. Metrics known as key performance indicators (KPIs) can be used to assess the extent to which a service's intended goals have been reached. The Federal Highway Administration defines KPIs as "milestones in or components of performance measures that serve as precursors to indicate progress toward the eventual achievement of the desired performance measures" (Garvin et al., 2011).

A comprehensive literature review of KPIs was conducted for both traditional transportation modes as well as transformative modes. This resulted in a compilation of several KPIs, all of which were sorted into five categories—operations; accessibility and equity; environmental, health and safety (EHS); economy; and policy.

This chapter begins by discussing KPIs that have been used for traditional modes of travel, and then follows with establishing the need for KPIs to exist and be applicable for transformative modes. Next, an inventory of both existing (i.e., in use) and proposed KPIs and their applications follow. Finally, KPIs that have been used for traditional modes are assessed to determine their applicability for tracking transformative modes, resulting in a selection of KPIs suitable for the transformative transportation modes involved in this study.

2.1.1 KPIs Used with Traditional Transportation Modes

KPIs are conducive to this project's goal of foreseeing the travel patterns that are expected to occur throughout Indiana in the coming years. The success of a transportation mode, at least in terms of this project, is largely based on the mode's resilience against factors that could inhibit its usefulness and based on its replicability to other regions outside of Indiana. Understanding the KPIs that are used to assess existing and "traditional" transportation modes (e.g., public transit, private vehicle) can help transportation agencies to better predict what effect transformative transportation modes (e.g., ride-hailing, bike-sharing, shared e-scooters, micro-transit) will have on the region's transportation landscape.

KPIs that have been used to evaluate traditional modes may require modifying to be applicable to disruptive modes; some of the traditional KPIs may be irrelevant to the assessment of disruptive modes entirely. For this reason, the search for KPIs was conducted by scouring proposals and reports on transit agencies' websites to discover what KPIs were being used in practice. Furthermore, research papers were dually consulted to learn what KPIs are being proposed but are not yet in use.

Aspects of a region such as population size and vehicle ownership rates were found to produce differing transformative transportation user characteristics (Shaheen & Cohen, 2018) and could, therefore, inform the extent to which the service can be used. Other studies have sought to evaluate multiple KPIs simultaneously to get a more well-rounded view of why certain modes are preferable over others to various demographics. For instance, the mobility energy productivity (MEP) metric developed by the National Renewable Energy Laboratory (NREL) encompasses mode availability, sustainability, and affordability evaluations with geospatial analyses (NREL, 2019). NREL's MEP metric also considers the number of destinations within a given drop-off location. "Number of destinations" is particularly relevant to transit users since the location of transit stops is rarely the same as the users' origin and destination locations.

2.1.2 Developing KPIs to Use with Transformative Transportation Modes

KPIs assessing the effectiveness of transit and other traditional transportation modes mentioned in Chapter 2.1.1 are not necessarily applicable to transformative modes. However, there is still a need to evaluate these new modes, so it is imperative that suitable KPIs be created for them. The STEPS framework, for instance, seeks to evaluate the effectiveness and equitableness of transformative transportation modes by assessing the systems from spatial, temporal, economic, physiological, and social contexts (Shaheen et al., 2017). This study highlighted KPI metrics that are especially relevant to new transformative transportation services (e.g., ride-hailing, bike-sharing, shared e-scooter).

User demographics, especially age, race, gender, income, and car ownership, are used by transportation agencies to measure various equity-related attributes of transportation services. For instance, a region with low car ownership rates may benefit from transit service more than a region with higher car ownership rates, so transit agencies may prioritize creating transit routes that cater to the car-scarce population. Shaheen and Cohen also discovered that certain demographics used transformative transportation services more often than others. Their study showed that carsharing services were most common in high-income areas (Shaheen et al., 2017). This could be attributed to the cost of using carsharing services, and while many of these services are partnerships between private and public agencies, the operation costs are not entirely subsidized. Therefore, installing the service in an area where the users can pay a premium price can be seen as necessary. Shaheen and Cohen (2018) also found that the outreach and advertisement initiatives done by these transformative transportation companies were seldom produced in a language other than English. This could also partly explain why white, non-Hispanic males were found to be the demographic who utilizes these services the most. These findings reinforce how KPIs relating to user demographics can not only help transportation companies and agencies predict which populations will utilize their service, but also the populations which may be facing some sort of barrier to using the service.

A service's usability can also heavily depend on the adequacy of the infrastructure to support it. In some cities, curb extensions (also called bulb-outs) and bus lanes may be needed for efficient transit operation, especially in cities that frequently experience traffic congestion. KPIs relating to the adequacy of a transit system's operational facilities can be modified to suit transformative modes as well. For example, some shared e-scooters and shared bikes have docking stations. Docking stations are analogous to transit stations because the user needs to walk to and from the stations to access the vehicle and walk from another docking station to reach their final destination. Therefore, KPIs which have been used for assessing the quality of transit systems may also be applicable to these docked, shared modes.

Shared bikes as well as shared e-scooters may not be permitted on sidewalks, so bike lanes may be critical for the safe operation of these modes. KPIs which quantify aspects of the built environment surrounding the mode's service area can help inform where these modes may be operated. For example, KPIs which quantify the miles of bike lanes or the percentage of the road network that is equipped with bike lanes can provide insight into which neighborhoods may utilize the bike-sharing service most. It could also help to explain which destinations users may or may not be willing to reach using the mode.

The newness of these transformative modes has resulted in city and transportation planners attempting to create and implement regulations without adequate knowledge of how to measure the success of these systems. Much research has sought to cross analyze the practices used by existing transportation agencies and companies in hopes of making them applicable to transformative modes. For instance, the practices used by ride-hailing, taxi and other ride-hailing companies were examined in a single study to understand the best means of regulating shared transportation services (Joshi et al., 2019). A conclusion from this study was that transformative transportation companies should be mandated to share their data. This allows researchers and industry professionals to accurately understand the trends that occur within certain modes. Other conclusions from this study pertain to the effect of transformative modes on traditional modes. Incentivizing the use of non-fuel-powered modes by making private vehicle use less attractive of a mode is an example of how transformative modes can impact traditional modes (Joshi et al., 2019). KPIs relating to the reduction in greenhouse gas emissions which result from the swapping of fuel-powered modes for non-fuel-powered modes can help to quantify and track the environmental and health impacts of such transformative modes. Conversely, transit agencies and transformative transportation companies often strive to have their services complement one another instead of competing with one another. Placing shared bike and e-scooter stations near transit stops is an example of how traditional modes have also affected transformative modes.

All transportation modes have something to offer and cater to different groups for different reasons. KPIs can help transportation professionals to understand how successful and replicable these services are, and ensure they are optimizing their reach.

2.2 Inventory of Available KPIs

2.2.1 KPI Categories

The KPIs in Table 2.1 are some of the most referenced KPIs among all the literature reviewed for this project. Many KPIs have the potential of fitting into more than one category. For instance, a KPI which assesses whether a bike-sharing program's service area allows for safe operation of the bikes can fall into both operations and EHS categories. Nonetheless, each KPI category has fairly distinct differences as described below.

The operations category contains KPIs which mainly assess efficiency of a service from the backend. In other words, these KPIs are mostly affected by the owners or managers of the system, not the system's users. Examples of operations KPIs may include the cost of using the service, the size of the service's fleet, and the number of miles of operating facilities (e.g., bus lanes, sidewalks) the service can operate on. Other operations KPIs may consider the spatial and temporal restraints of a system (e.g., service areas or service operating times).

The accessibility and equity category involves KPIs such as trip origins and destinations as well as user adoption. Such metrics can help transportation agencies to discover if the service is reaching their intended market, or if there may be unknown factors hindering the target demographic's/market's accessibility to the service. Reasons that are not related to accessibility could also be the reason an agency's target demographic or expected market does not utilize the service. If the materials advertising a service have only been created in English or have only been distributed on social media and other online platforms, non-English speaking groups as well as technologically disadvantaged groups may not use the service because they do not understand it, or they are unaware that the service even exists. KPIs in this category may also strive to assess which demographics may be disproportionately affected by undesirable or burdensome effects of a service.

The EHS category includes environmental KPIs such as the suitability of the built environment, health KPIs such as the percentage change in fuel emissions, and safety KPIs such as crash rates. The economy category pertains to the financials of a service. For example, the farebox recovery ratio, or the ratio of a system's total generated fare to its operating and maintenance costs, is an economy KPI. KPIs can also measure setbacks to reaching an agency's performance measures, such as a loss in revenue that may result from construction on a major road or a major shift in public opinion.

The category for policy KPIs is perhaps the broadest of the five. Policy KPIs may quantify the number of funding sources a service relies upon, or the number of stakeholders involved in the rulemaking process. One of the KPIs most relevant to this study is the quantification of metrics tracked. Many transformative modes, shared bikes and shared e-scooters in particular, not only track the characteristics of trips made by their fleet (e.g., origin and destination, start and end time), but also have this information readily available as well. Unfortunately, these metrics were/are seldom tracked for traditional modes such as public transit and taxi services. Studies that aim to predict what transportation behaviors and patterns may be in the future need to first understand how transportation modes are being used currently and how they have been used in the past.

Therefore, it is imperative that transportation agencies and companies invest time and resources into quantifying various aspects of their services.

2.2.2 Explanation of Unique KPIs

The KPIs in Table 2.1 can be applied to both traditional and transformative modes, namely, public transit, ride-hailing, bike-sharing and shared e-scooters. The feature that the KPIs mentioned in Chapter 2.1 measure may be easily understood from their KPI names because they are quite inferable. However, other KPI names may be less intuitive. *Usage rate*, for example, is a ratio of the number of daily trips to the size of the service's fleet. *Market penetration* is the ratio of the number of users of a service to the number of potential users of that service. Potential users are typically considered to be the people who reside near the service's operating area. Closely related is the *user adoption by demographic* KPI. It is a ratio of the users of a particular demographic who use the service to the number of potential users of the service who fall in that same demographic. An example of this KPI would be dividing the number of Hispanic ride-hailing users by the total number of Hispanic people in the service area. *Severity of crashes* examines the extent of crashes involving the transportation mode in question using the KABCO injury classification scale (FHWA, 2018). *Farebox recovery ratio* is a KPI that divides the funds a service generates by its operating and maintaining expenses. This KPI has been used to evaluate the revenue transit agencies bring in, hence the word *farebox* in its name. However, other services that may not have a physical farebox but still require payment to use (e.g., ride-hailing services) can still benefit from this KPI. *Number of funding sources* assesses how much financial assistance is provided to owners and/or operators of the service from parties outside those who own or operate it. Services that have more stakeholders involved in their tracking and evaluation processes may be more successful in their operation, especially if those stakeholders provide standards for the service's owners and operators to be held accountable to. Stakeholders may even be fined or required to return some of the money they earned from the project if the service does not reach its intended goals (Garvin et al., 2011; Pula et al., 2015). This incentivizes stakeholders to be invested in the project's success beyond its implementation. The *number of stakeholders* KPI is a count of how many stakeholders or interested parties are involved in the progression of the service, especially after the service's implementation stage.

2.3 Selection of KPIs Suitable for Transformative Modes

The KPIs in the operations, accessibility and equity and EHS categories were deemed to be the most relevant to this project. Table 2.1 shows the nine KPIs that were selected for evaluating the transformative modes included in this project.

We felt it was necessary to understand the capabilities of each mode, so KPIs assessing the operations were selected. The *usage of service* KPI includes/involves the number of unique users using the service every day, the start and end times of trips, and locations for where the service is being used. It also includes more behavioral data such as the users' trip purpose while utilizing the service as well as why they prefer using the service to other services. Also, within the operations category, *fleet size* was included to determine whether the correct number of vehicles were acquired for the respective service area. Finally, the *integration with other modes* KPI assessed how well the service integrates with the existing transportation modes and related infrastructure (e.g., the bike lanes or transit network).

TABLE 2.1
Inventory of key performance indicators

Operations	Accessibility + Equity	EHS	Economy	Policy
User cost per trip	Access to vehicles	Added/replaced trips	Congestion	Number of funding sources
Memberships available	Number of pick up and drop off locations	Adequacy of built environment	Farebox recovery ratio	Number of stakeholders
Number of registered users	Average distance between pick up and drop off locations	Distance to pick-up location (first mile)		Data collection
Fleet size	Trip origins and destinations	Distance from drop-off location (last mile)		Open data
Geographic area of service	Access to necessities	Crash rate		
Integration with other modes	Portion of fleet that is wheelchair accessible	Severity of crashes		
Operating hours	Market penetration	Safety of infrastructure		
Operating months	User adoption by demographic			
Average trip distance				
Usage of service				
Usage rate				

The next KPI category we pulled KPIs from is *environmental, health and safety*. These KPIs assess the overall safety and sustainability of the mode. For instance, the "safety of infrastructure" KPI examines whether new infrastructure is needed for users to safely operate the new mode, like a designated e-scooter path. The *adequacy of built environment* KPI investigates whether new infrastructure, such as docking stations or turnouts, needs to be built in order to maximize the use of the service. Furthermore, the reduction in vehicle emissions that results from fuel-powered modes being swapped for non-fuel-powered modes is of great significance to environmental agencies and others who believe it is important to reduce greenhouse gas emissions. The affordability, ease/feasibility and prevalence of certain transformative modes can also result in people traveling more frequently. This can cause an increase in vehicle emissions and congestion on roads. Therefore, the *added/replaced trips* KPI was also selected.

The *accessibility and equity* KPI category was found to be crucial to this study as well. KPIs such as *access to vehicles* and *access to necessities* look at how feasible it is for various demographics to reach the service's vehicles, and how feasible it is for those users to reach essential services (e.g., jobs, schools, grocery stores, healthcare facilities) with that vehicle. The *user demographic* KPI aims to discover which demographic of people are using the mode, especially in terms of race, age, and English-speaking ability. This KPI can inform transit agencies and similar planning and policymaking agencies on which demographic utilizes the mode the most, as this may suggest that certain aspects of the mode cater to a particular demographic more than another.

Lastly, the *open data* KPI from the *policy* category was perhaps the most relevant KPI in the study since the agent-based model being developed for this study relies heavily upon robust, easily accessible data pertaining to transportation modes and travel behaviors. Data useful to this study include the locations in which the various transportation services are being utilized as well as the services' peak days and peak hours of operation.

2.4 Chapter Summary

With careful analysis and selection, three main categories of KPIs were suggested to evaluate the performance of transformative transportation systems. These include *operations*, *accessibility + equity*, and *environmental, health and safety* (EHS). These KPIs are used throughout the different sections of the report to help understand the impacts of different transformative services across Indiana cities. For instance, Chapter 3 uses system-level and trip-level data (such as fleet size, trip distance, trip count, and usage) to examine the change in KPIs pertaining to the *operations* category across the different systems in Indiana cities. Additionally, *accessibility + equity* KPIs (such as vehicle availability and user demographics) are considered in the design of the two survey studies for the Greater Lafayette Area (Chapter 5.1) and Indianapolis (Chapter 5.2) and subsequent data analysis, to evaluate the impacts on social equity. In Chapter 6 and Chapter 7, the "EHS" KPI is evaluated for transformative transportation systems in Indianapolis, focusing on the mode substitution between public transit and private vehicle usage. In addition, the importance of *open data* KPI is also discussed in the implementation plan (Chapter 8.2).

3. UNDERSTANDING THE USAGE PATTERNS OF TRANSFORMATIVE TRANSPORTATION TECHNOLOGIES IN INDIANA

In an effort to understand how transformative transportation technologies are currently used in Indiana, this chapter examines the usage patterns of the systems based on historical data. Three case study cities (Indianapolis, Bloomington, and Greater Lafayette Area) were chosen for this analysis because of their well-development of transformative transportation technologies. Indianapolis is the state capital and the most-populous city of Indiana, which sits in the Marion County. The Greater Lafayette Area and Bloomington are campus cities, where the travel patterns could be different. The operation status and data availability of each system are listed in Table 3.1. Based on the available data, this chapter analyzes the bike-sharing and shared e-scooter systems in Indianapolis, the bike-sharing system in the Greater Lafayette Area, and the shared e-scooter system in Bloomington. The information gap of other systems is filled by the surveys introduced in Chapter 5.

3.1 Bike-Sharing and Shared E-Scooter System in Indianapolis

3.1.1 Overview of the Bike-Sharing and Shared E-Scooter Systems in Indianapolis

Indiana Pacers Bikeshare System is a station-based bike-sharing system operated in Indianapolis. Pacers bike-sharing started service in April 2014 and the system currently offers about 580 bikes with 50 stations and 750 docks. The system provides a public available API to collect station status data to track the system usage (NABSA, 2020). The station status data includes a unique station ID, station location (in longitude and latitude), available docks, and available bikes for each station at data request time. We collected the station status data every 2 minutes using the public application programming interface (APIs) provided by the Pacers bike-sharing from September 2019 to December 2020. The use of bike-sharing could be inferred from the change of the number of available docks at a station due to bike pick-up or drop-off. For example, if the number of available docks in a station was increased by one compared with the previously recorded data

TABLE 3.1
System operation status and data availability in the three case study cities

Cities	System	Operation Status	Data Availability
Indianapolis	Bike-sharing	In operation	System level
	Shared e-scooter	In operation	Trip level
	Ride-hailing	In operation	N/A
Greater Lafayette Area	Bike-sharing	Terminated	Trip level
	Shared e-scooter	In operation	N/A
	Ride-hailing	In operation	N/A
Bloomington	Bike-sharing	Terminated	N/A
	Shared e-scooter	In operation	System level
	Ride-hailing	In operation	N/A

(e.g., 2 minutes ago), there should be a bike-sharing trip starting from this station between the two data collection periods. By tracking all station statuses, we can estimate the unlinked bike-sharing trip count that started or ended at each station and analyze system usage. However, without the information of the linked trips, we cannot analyze trip patterns, such as trip distance, trip duration, etc.

Two shared e-scooter companies, Bird and Lime, have been operating shared e-scooters in Indianapolis since June 2018. We have obtained trip data which spans from September 2018 to December 2020 and consists of over two million trip records. Each trip record includes a unique trip ID, an e-scooter ID, trip start and end time, coordinates of trip origins and destinations, trip duration (in seconds), and trip distance (in miles, calculated based on GPS trajectory by the system operator). We cleaned the data to exclude outliers such as very short trips (<0.02 miles) that may be recorded when the users immediately returned an e-scooter after pickup (possibly due to having a malfunctioning unit), or an extremely long trip (>10 miles, possibly recorded due to the user forgetting to end the trip in the app). With the trip OD information, we can evaluate the system usage and trip patterns.

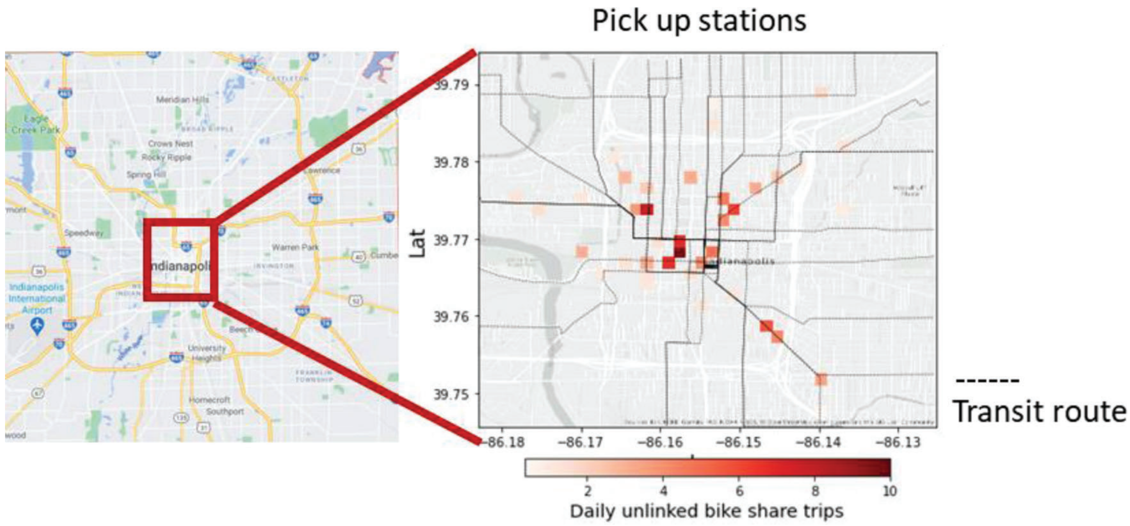
3.1.2 System Usage Patterns

To understand how the bike-sharing system in Indianapolis is currently used, we analyzed the system usage patterns based on the station status data from September 2019 to February 2020 (this analysis only covered the period before the COVID-19 pandemic. Impacts of COVID-19 will be discussed in Chapter 4). Figure 3.1a shows the station distribution of Pacers bike share system and the average daily trip count. Most of the 50 stations are set along the bus lines, indicating the potential to integrate with the transit system by serving as the first-/last-mile connection. The average daily trip count ranges from 2 to 10 trips per station and stations close to the city center could serve more trips per day. Figure 3.1b shows the temporal distribution of bike-sharing trips within a day across different months. We found that there is a morning peak at 8 am and an afternoon peak from 4 pm to 5 pm during the study period. The two peaks indicate that bike share users may use the system for commuting purposes, relieving the automobile traffic burden in peak hours. Due to the impact of cold weather, trip counts significantly decreased during the wintertime.

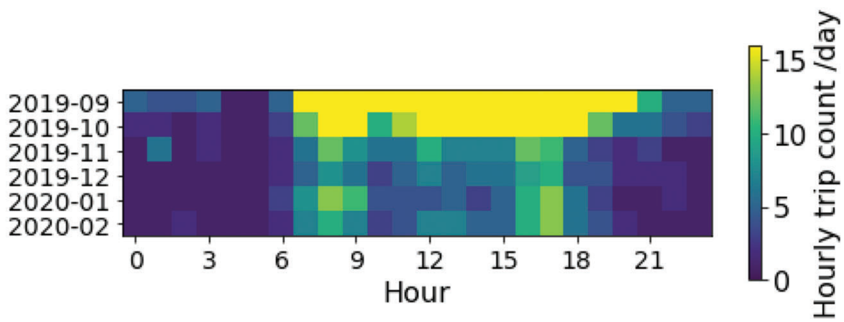
The shared e-scooters are mainly available in the downtown area of Indianapolis (Figure 3.2a), with similar spatial coverage to the bike-sharing system. Most of the trips (over 68%) started from downtown. Downtown is also the city's transportation hub where almost all bus lines converge, showing overlapped service coverage by the two systems. The average number of trips in a day ranged from 1,200 to 7,000, with the highest demand in October and the lowest in February (Figure 3.2b). On a given day, most of the trips occurred between 12 pm and 9 pm, with an evening peak from 4 pm to 7 pm and no morning peak (Figure 3.2c). Our observation of the e-scooter usage pattern is consistent with another study focused on Indianapolis (Mathew et al., 2019). The e-scooter usage pattern varies at different times of the day, which may lead to temporally heterogeneous relationships between the two systems. On average, about 37%–68% of the e-scooters were repositioned each day, and the same e-scooter may be repositioned more than once. Most of the e-scooters were redistributed downtown (Figure 3.2c), leading to the concentrated system usage observed in Figure 3.2a.

3.2 Bike-Sharing System in the Greater Lafayette Area

The bike-sharing system in the Greater Lafayette Area (Pace System) is a hybrid system, which had 20 fixed bike-sharing stations around Purdue Campus for pick-up and drop-off, but also allowed riders to freely park the bikes in the service area. The Pace System was terminated in the fall of 2019. We obtained trip-level data from August to November in 2018, including trip OD, trip start and end time, and bike id. Figure 3.3a shows the spatial distribution of daily trip demand. Most trips started from Purdue



(a)



(b)

Figure 3.1 (a) Pacers' bike share stations and average daily trip count, and (b) hourly trip count of Pacers bike-sharing.

Campus and Student Hostel, indicating higher use by students. During the daytime, trip demand is relatively stable compared with Indianapolis, because there is no clear traffic peak within the campus area (Figure 3.3b).

3.3 Shared E-Scooter System in Bloomington

Bloomington launched two shared e-scooter systems, Bird and Lime, starting in September 2018. We accessed the daily summary data for both systems from April 2019 to February 2020, including the daily fleet size and trip count. Figure 3.4 shows the daily trips and fleet size of Bloomington e-scooter system. The daily trip ranges from 700 to 3,500, and the total daily fleet size ranges from 300 to 700. We found that fall time was a high-demand season of the year. Unlike Indianapolis (Figure 3.2), which has higher demand from May to June, demand for Bloomington is smooth until July. It could be because of the summer break that a campus city may be more sensitive to, and higher demand is observed when students are back to campus during the fall.

3.4 Chapter Summary

Trip count, fleet size, and usage rate are three important KPIs to measure the operation of transformative transportation systems. The usage rate, which is the average trip count served by one fleet unit, is the key index for operators and city planners to measure the system efficiency. We compared the daily trip count, daily fleet size, and daily usage rate of shared e-scooter and bike-sharing systems in three case study cities (Figure 3.5).

When comparing bike-sharing and shared e-scooter systems, in general, shared e-scooter systems are much larger than bike-sharing systems in Indiana cities. The e-scooter fleet size in Indianapolis ranged from 500 to 2,500 and fleet size in Bloomington ranged from 250 to 700. Bike-sharing systems in Greater Lafayette Area and Indianapolis are much

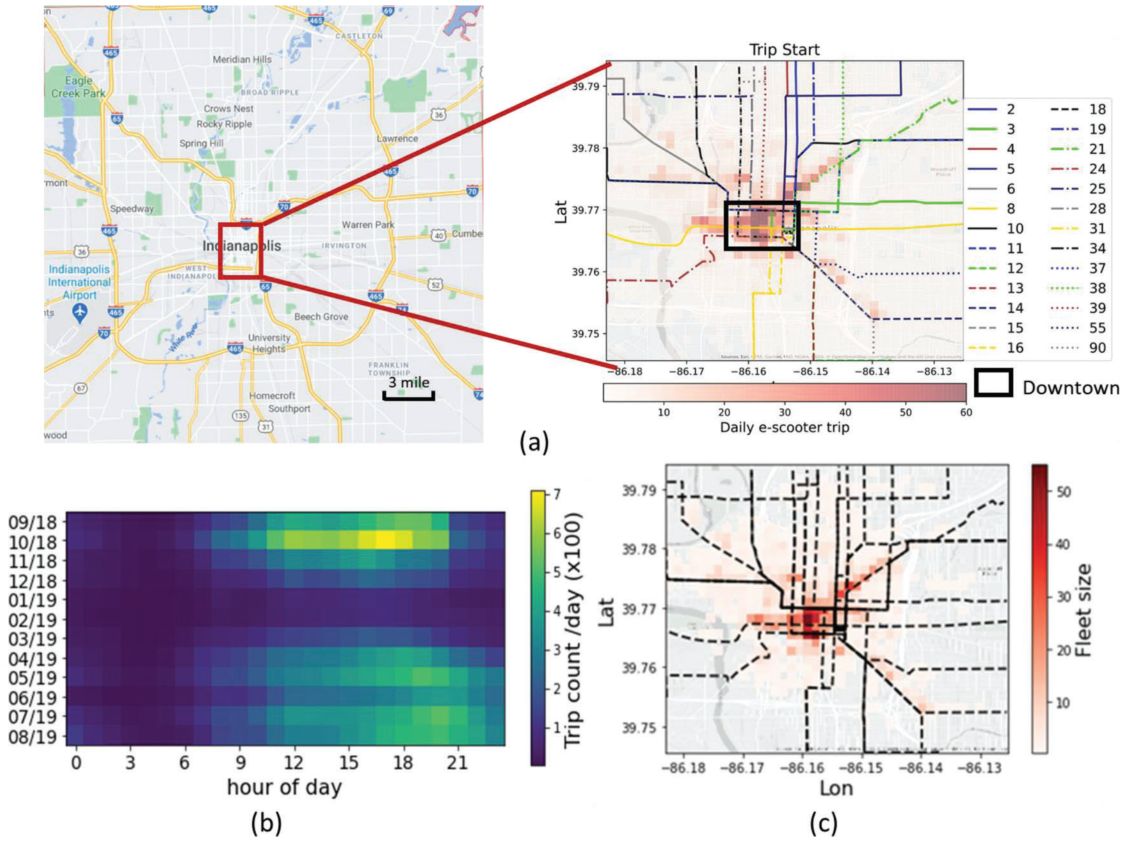
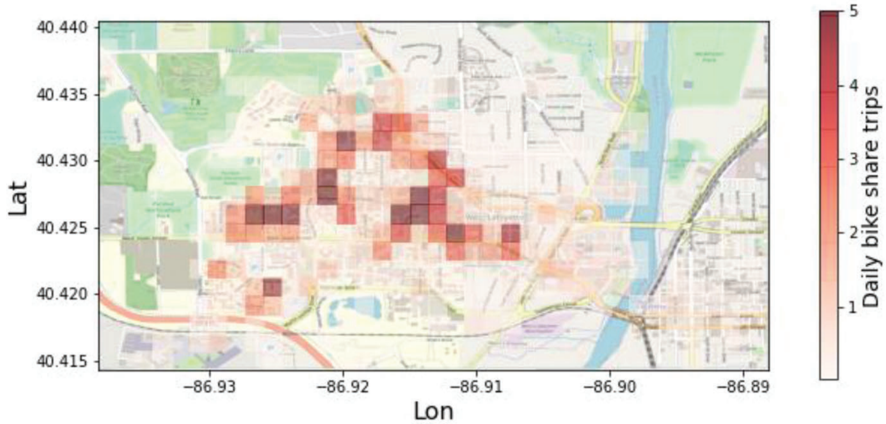


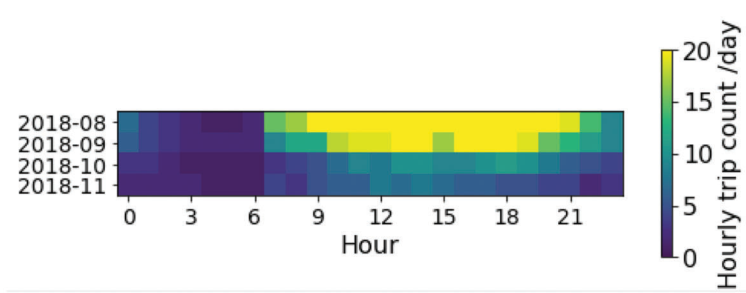
Figure 3.2 The spatial and temporal patterns of e-scooter trips, utilization rate, and repositioning. (a) Case study city (Marion County) and the main e-scooter service area with heatmap of the daily average starting from each grid. Different lines represent different bus lines. (b) Hourly average trip count variations by month. (c) Destination distribution of repositioned e-scooters. The color of each grid is determined by the average daily number of e-scooters moved to this grid.

smaller, with less than 100 and 400 bikes, respectively. With the higher fleet size, shared e-scooter systems can also serve many more trips than bike-shared systems. In Indianapolis, a shared e-scooter system can serve 1,000 to 7,000 trips in a day, while the bike-sharing system can only serve less than 500 trips. On average, each shared e-scooter can be used about three to four times per day. But each shared bike can only serve less than one trip per day, showing its lower usage rate and system efficiency. Shared e-scooter operators would adjust the fleet size for different seasons to meet the changing demand, but bike-sharing operators did not take back a part of bikes during the wintertime.

In addition to the different patterns for different systems, the same system may also have different usage patterns in different cities. The shared e-scooter system in Indianapolis had a higher demand in May, June, and July, and operators launched more e-scooters to satisfy the demand. However, Bloomington, a campus city, had a lower demand from May to July during the summer break when students left the campus and demand decreased. Therefore, Bloomington operators also decreased the e-scooter fleet size because of lower demand. The various patterns for different systems in Indiana cities suggest that city planners and system operators should design and manage the systems based on system-specific real-world data.



(a)



(b)

Figure 3.3 (a) Purdue Pace bike share daily trip count, and (b) trip count by time of day.

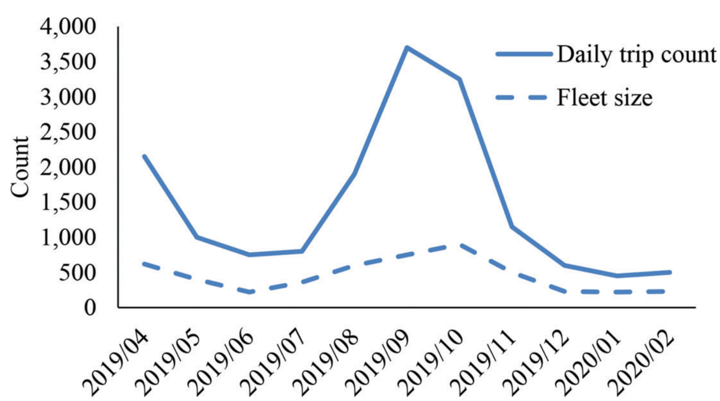
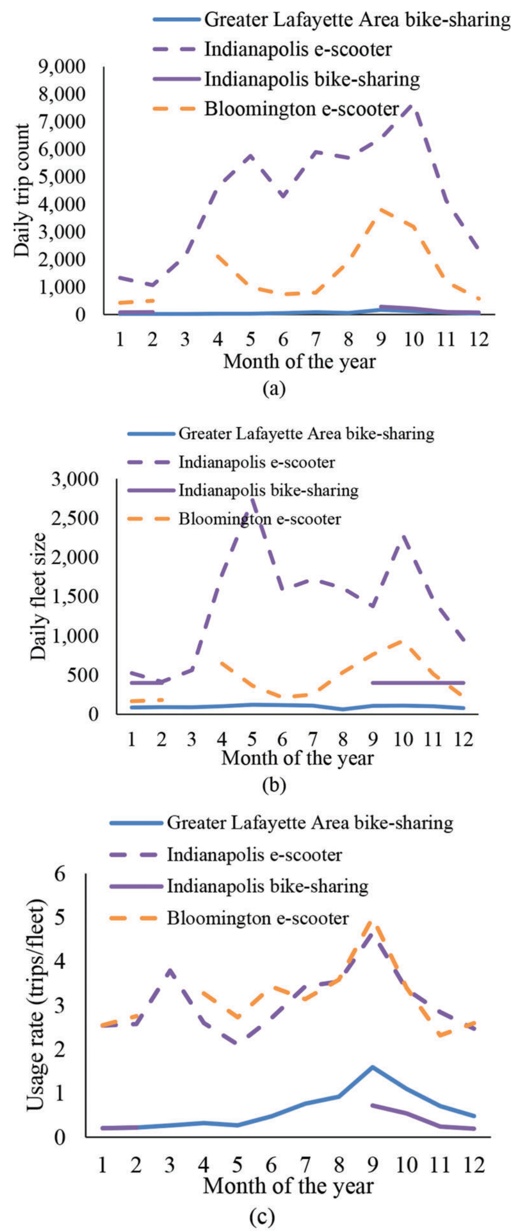


Figure 3.4 Daily trip count and fleet size of shared e-scooter systems in Bloomington.



Note: Due to the different temporal coverage of available data, this figure combines data from 2018 and 2019 into a 12-month range to represent the monthly pattern, assuming patterns in 2018 and 2019 are similar.

Figure 3.5 System usage patterns for bike-sharing and shared e-scooter systems in Indiana cities. (a) Average daily fleet size for each month, (b) average daily trip count for each month, and (c) average daily usage rate for each month.

4. THE IMPACTS OF COVID-19 ON SYSTEM USAGE

4.1 Covid's Impact on Traditional and Transformative Transportation Systems

From stay-at-home orders to social distancing protocols, the COVID-19 pandemic has had a substantial impact on the transportation field. It is also evident that the pandemic will have lasting effects on transportation services and users' behaviors. While this study is being conducted during the pandemic, this chapter aims to provide context about how transportation has fared in the beginning, middle, and final stages of the pandemic. *Beginning* signifies the spring and summer of 2020, which is when the World Health Organization (WHO), Centers for Disease Control and Prevention (CDC), and U.S. governments began imposing restrictions due to the severity of the pandemic. *Final* refers to the spring and summer seasons of 2021, when vaccines for the coronavirus were being administered and the CDC began to relax some of its strictest COVID-19 regulations. *Middle* refers to the time between the beginning and final stages (i.e., fall and winter of 2020). Reports and articles about COVID-19 and transportation will be summarized in this chapter. The popularity of six destination types throughout the pandemic (shown in Figure 4.1) is also discussed in reference to state and nationwide orders and events related to the pandemic. All trip destination charts in this chapter are from Our World in Data (2021). The events on all timelines in this chapter are from WFYI Indianapolis' COVID-19 Timeline webpage (Jaggers, 2021).

4.2 Covid's Impact on Transportation During the Beginning Stages of the Pandemic

Both traditional and transformative transportation modes endured enormous shifts in use and operation during the pandemic. At the beginning of the pandemic, several public transit agencies were forced to operate their fleets at reduced capacities due to social distancing mandates and other orders imposed by city and state leaders. The Pennsylvania Port Authority, for example, suffered more than 75% decrease in ridership as a result of Governor Tom Wolf's stay-at-home order and consequently reduced service by about 25% (Blazina, 2020). Other reasons for reductions in transit ridership may have been attributed to transit users' fear of contracting the deadly coronavirus from fellow passengers in a transit vehicle. This thinking may be the reason Lyft's ridership was down 75% in April 2020 compared to April 2019 (Lekach, 2020). Several other ride-hailing companies also halted their shared ride services (e.g., UberPool) which allowed drivers to pick up several passengers on the way to a final destination (Broderick, 2020). Shared modes of transportation were not the only modes affected by the pandemic. In Wisconsin, weekend traffic decreased 60% and the idea of repurposing select Wisconsin streets for bicycle use and walk use surfaced (Graber, 2020). The reduction in traffic on New York City's streets led to an astonishing decrease of 71% and 56% in pedestrian and cyclist crashes, respectively (Shaheen, 2020). Furthermore, in March 2020 the user demographic of New York City's Citi Bike bike-sharing program hit a record high of 53% women (Goldbaum, 2020). This change in user

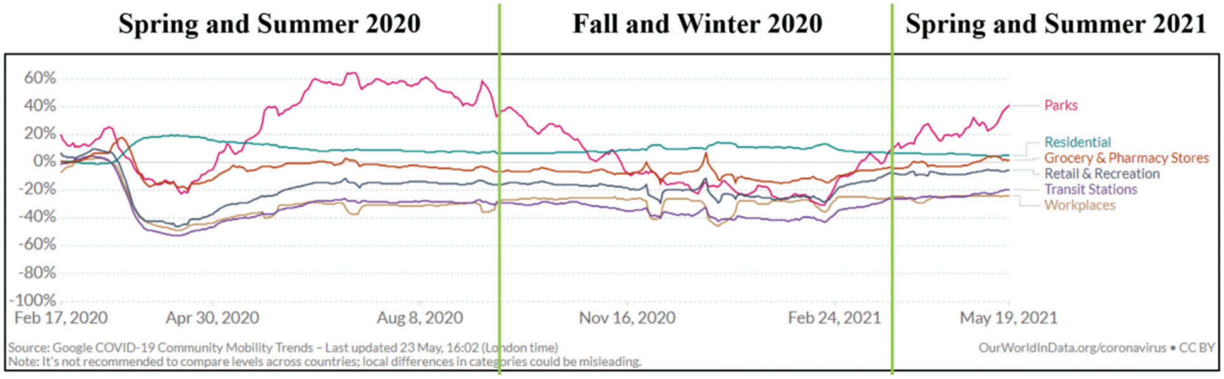


Figure 4.1 Deviation in trip destination frequencies throughout the pandemic.

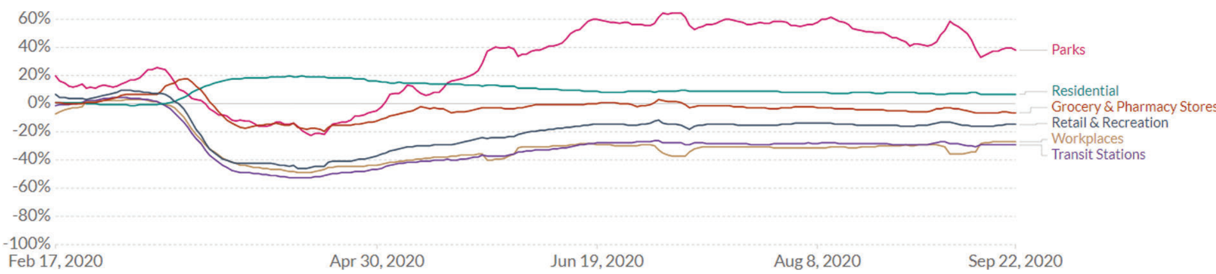


Figure 4.2 Deviation in trip destination frequencies (beginning stages of pandemic).

base is likely due to women serving in the healthcare industry and other essential roles.

4.2.1 Pandemic's Unequal Effects Across Various Demographic Groups

While this pandemic has altered the lives of many, it has also shined a light on a multitude of divides (e.g., racial, wealth, social class) within the U.S. and globally. By taking note of the groups that used certain transportation modes during the pandemic, as well as the groups that refrained from using certain modes, transportation companies and agencies can better understand who their most unwavering clients are. Understanding which groups use certain modes, especially modes that are undesirable due to factors caused by the pandemic, provides great insight into which populations these companies should ensure they are servicing. A paper by Tirachini and Cats (2020) stated that public transit had "taken the hardest blow out of all transportation modes." It also mentioned that transit use decreased for higher-income groups by more than 70%, but only decreased between 30% and 40% for those in lower-income brackets. Lower-income groups tend to have low car ownership rates, and they also tend to work in service jobs which may not allow for the flexibility of working from home (Escobari et al., 2020). Both of these traits likely result in public transit being viewed as a "necessary evil" for low-income people and other groups that consider transit their primary mode of travel.

In addition to transportation companies altering how they operated their services; the users of these services also changed their travel patterns and behaviors. Figure 4.1 above depicts the change in popularity of six different trip destinations over the course of the pandemic—parks, residential, grocery and pharmacy stores, retail and recreation, workplaces, and transit stations. Figure 4.2 shows these patterns for the beginning phase of the pandemic. The frequency in which places were visited did not deviate significantly from pre-pandemic frequencies until around the middle of March. This coincides with the dates that many governors around the U.S. implemented state shut-downs (Figure 4.3). It should be noted that the plot for residential shows the percent change in duration at residences, not the percent change in trips to residences. The time people were spending at their residences increased by approximately 20% from mid-March to the end of April. This may be attributed to many workplaces adopting a remote format that allows employees to work from their homes. The need to travel to a jobsite may have been the reason many people decided to leave their homes at all during the day. Now that commuting trips were no longer necessary, employees may have resorted to making shorter trips (e.g., a quick run to the grocery store where they come back home immediately) as opposed to visiting multiple places in succession.

The other five destinations all experienced drops in how often they were frequented, especially transit stations, workplaces, and retail and recreation locations. Many state shutdowns required non-essential

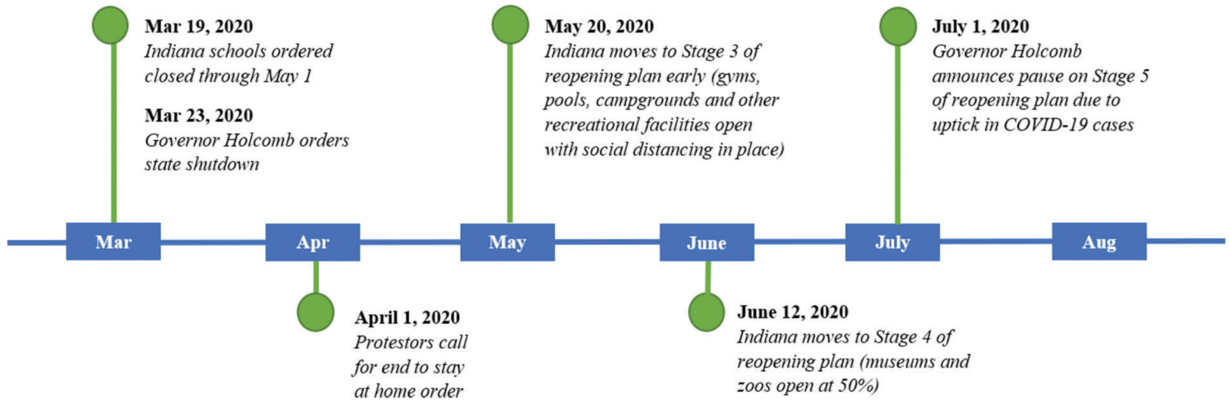


Figure 4.3 Timeline of COVID-19-related events in Indiana (beginning stages of pandemic).

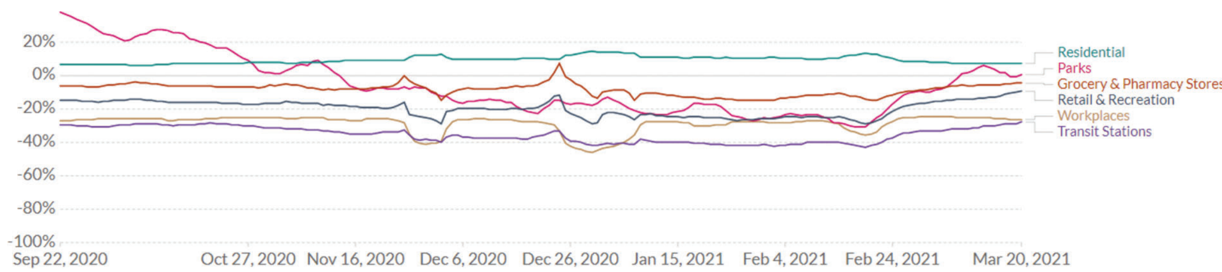


Figure 4.4 Deviation in trip destination frequencies (middle stages of pandemic).

businesses to entirely cease operations, and many retail and recreational venues fall into the non-essential category. Grocery and pharmacy stores' drop in frequency was about half that of the retail and recreation locations, most likely because they were allowed to remain open even if they had to adjust their operating hours. Towards the end of April, many people were beginning to feel restless from spending so much time in their homes and not being allowed to enjoy the pleasures in life they had before the pandemic occurred. Figure 4.2 also shows that around this same time frequencies of visits to all destinations began to tend towards baseline (i.e., pre-pandemic levels). All destinations except residential steadily tended towards baseline levels around the end of April, and visits to parks surpassed even pre-pandemic levels. During the first week in July, visits to parks reached over 60% higher than baseline levels, and visits to workplaces were almost 40% lower than baseline levels. This may be attributed to people taking time off from work to make a long weekend out of the Independence Day (July 4th) holiday. This holiday is traditionally celebrated with grilling food outdoors so this could also explain the uptick in park visits around this time.

4.3 Covid's Impact on Transportation During the Middle Stages of the Pandemic

Travel to parks and outdoor spaces decreased staggeringly during the middle of the pandemic, presumably because of the seasons' low temperatures (Figure 4.4). Trips to grocery and retail locations as well as transit locations increased sharply around the Christmas holiday. Christmas is typically a time when people have loved ones over their home to enjoy a home-cooked meal, and give them gifts, so this explains the increase in grocery and retail visits. The increased visits to transit stations may be a result of people traveling to visit their family and friends. Other reasons people may have traveled for the Christmas holiday are that many states had entered the final stages of their reopening plan by this time, and the rollout of the coronavirus vaccine had begun in many parts of the U.S. including Indiana (Figure 4.5) (Jaggers, 2021).

By the middle of the pandemic, many transportation modes had adapted to a "new normal" of operating. Uber developed a partnership with Clorox, one of the largest U.S. brands for disinfecting products, which allowed Uber drivers to have a supply of disinfecting wipes upon request (Uber, 2020). Under Uber's "No mask, no ride" policy, riders and drivers were able to report if someone in the vehicle was not wearing a mask. Uber also required drivers to submit a selfie through the app to prove that they are wearing a mask. Transit agencies have also adopted new practices to ensure the safety of drivers and riders. By this stage in the pandemic, many transit vehicles were retrofitted with plexiglass shields on the right side of the driver's seat to provide an additional barrier between passengers and drivers, especially when riders are paying their fares (Dallas Area Rapid Transit, 2020). Micro-mobility modes such as shared bikes and shared

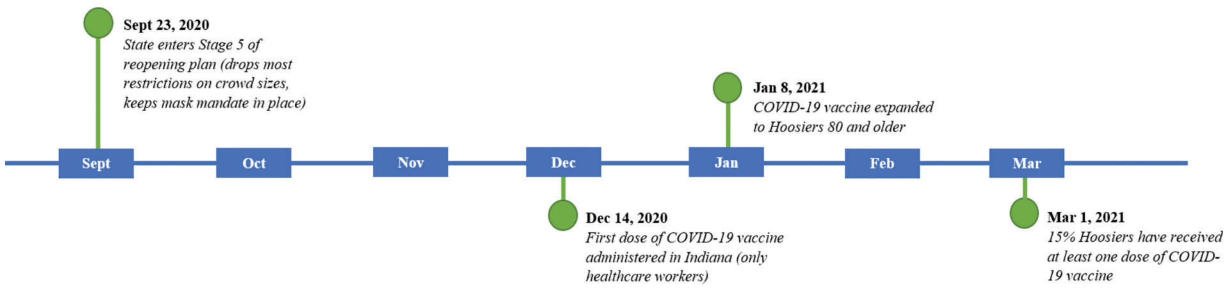


Figure 4.5 Timeline of COVID-19-related events in Indiana (middle stages of pandemic).

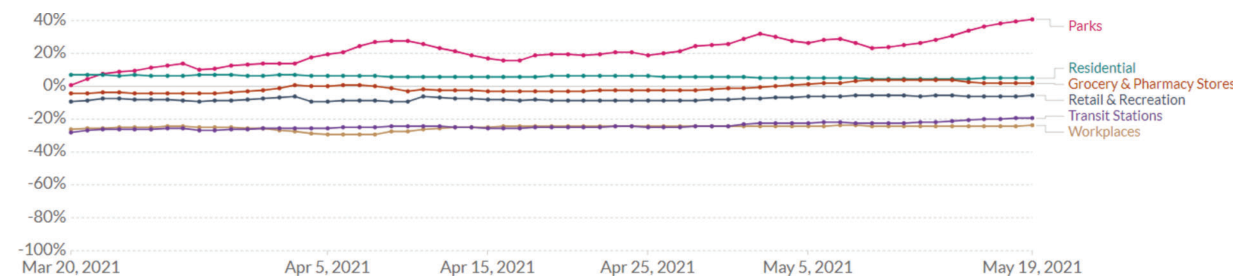


Figure 4.6 Deviation in trip destination frequencies (final stages of pandemic).

e-scooters were brought back to the streets and campuses they occupied prior to the pandemic. Spin, for instance, returned its fleet of e-scooters to Purdue University's campus and promised to perform a "nightly cleaning" before deploying the scooters the following day (Bangert, 2020). They also mandated masks be worn while operating the scooters and recommended that surfaces on the scooter be wiped down by the rider before use.

4.4 Covid's Impact on Transportation During the Final Stages of the Pandemic

The final stages of the pandemic are when travel trends and operations are most reminiscent of their pre-pandemic equivalents. Parks are surpassing pre-pandemic levels (Figure 4.6). This suggests that spending time outdoors, which was likely caused by the many restrictions people had to adhere to when gathering indoors, is a trend that is here to stay. Visits to transit stations and places of work are still down by approximately 20%. Trips to retail and recreation venues are down by about 10%, but grocery and pharmacy stores have nearly achieved their baseline levels.

The vaccine distribution (see Figure 4.7) and consequent decrease in coronavirus cases is likely the reason for people frequenting these destinations more often. Also, the CDC relaxed some of its strictest rules during these months. For example, plane travel within the U.S. no longer requires one to self-quarantine before and after the trip or get negative coronavirus test results. However, the CDC is still mandating that people wear masks when utilizing public transportation, including planes and transit (CDC, 2021). Transportation companies are also relaxing some of their COVID-19 restrictions while maintaining others. The Pennsylvania Port Authority, for instance, lifted capacity limitations on their transit vehicles but has maintained the rule that masks be worn by all riders, even those who are vaccinated (Ciccocioppo, 2021). Vaccine rollouts have impacted ride-hailing companies as well. Both Uber and Lyft are also still enforcing mask-wearing among drivers and riders, regardless of vaccination status. Both companies have also pledged to offer free or discounted rides to people wishing to get to a vaccine site (Chappell, 2021). Shared micro-mobility services are also being launched in new areas. Cycle is expected to launch in Encinitas, California in fall of 2021 (Henry, 2021). This particular service is replacing a bike-sharing program that was unfortunately forced to terminate its contract with the city due to circumstances related to the pandemic.

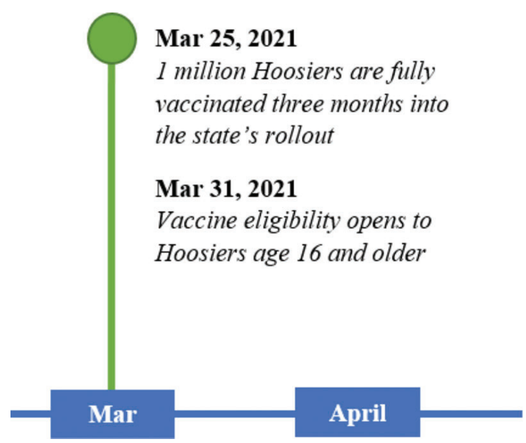


Figure 4.7 Timeline of COVID-19-related events in Indiana (final stages of pandemic).

4.5 Review of Related Literature

The beginning of the COVID-19 pandemic brought significant reductions in mobility. Mobility reductions, often more than 50%, were seen in cities during the first weeks of lockdown and travel restrictions (Warren & Skillman, 2020). Rasca et al. (2021) performed four case studies in Adger, Norway; Innsbruck, Austria; Vienna, Austria; and Oslo, Norway. In each case, reductions in transit ridership of up to 70% were observed. Smaller reductions were observed for rural areas. König and Dreßler (2021) found that 30.2% of those living in rural areas experienced changed travel behavior during the pandemic, mostly from reduced trips for commuting and leisure. The share of public transit is much smaller in rural areas so the impact on public transportation was also much smaller.

As the pandemic progressed, mobility patterns began to diverge more in different locations. Increases in mobility led some areas to have resurgences of COVID cases while case counts also continued to impact further changes in mobility (Chapin & Roy, 2021). Many cities that experienced second and third waves also experienced additional reductions in mobility. These later mobility reductions were often less severe than that from the first wave, despite higher infection rates during later waves (Rasca et al., 2021). Many cities also experienced increases in travel as infection rates began to drop and restrictions began to be lifted. Beck and Hensher (2020) found that in Australia there was a 50% increase in travel since initial reductions and that much of this travel included social and recreational travel. In addition to reductions in travel, Huang et al. (2020) showed that there is a negative correlation between venue check-ins before and after the pandemic, showing that travel patterns have changed significantly.

4.5.1 Pandemic's Impact on Transportation Mode Choices

The pandemic has also altered the way that people choose transportation modes. Reductions in transportation did not occur uniformly, with reductions in public transit falling by up to 80% as people reduced travel as well as shifting modes to walking, cycling, and private vehicles (Fumagalli et al., 2021; Munawar et al., 2021). Dingil and Esztergár-Kiss (2021) found that the probability of changing transit modes was 31.5 times greater for transit users than car users due to fear of infection on public transit. Reductions in public transit occurred across shared modes. Bus service in Trieste, Italy fell sharply to be replaced by walking, cars, and cycling (Scorrano & Danielis, 2021). Subway use fell in New York City by 69.7%, mostly from trip reductions and increased bike-sharing (Sy et al., 2020). Light and heavy rail use also dropped significantly, especially for those further from stations, and was replaced mostly by cars, walking, and cycling (Hu & Chen, 2021; Tan & Ma, 2021). Ride-hailing had a less uniform decline, often being viewed as more risky than private vehicles but less risky than traditional public transit options (Ozbilen et al., 2021). In fact, Dzisi et al. (2021) found that the mode share of ride-hailing rose from 30% to 59% in Ghana during the pandemic as part of a larger shift towards ride-hailing.

While public transit began to decline, many forms of individual and active transit began to grow, especially as travel restrictions loosened. Bike-sharing stands out as the form of transportation that has grown the most during the pandemic. Li et al. (2020) found that bikes are directly replacing other forms of public transportation that are considered riskier in Zurich, and that this has caused trip lengths to increase. Similarly, (Lock, 2020) found that reduced traffic in Sydney has also provided an additional incentive for cyclists and more people are reporting interest in improving the city's cycling infrastructure.

4.5.2 Pandemic's Impact on Trip Purpose

Primary trip purpose and travel destinations changed significantly due to the pandemic. Saha et al. found that visits to retail, grocery, transit stations, and workplaces dropped while visits to residential places increased because of the pandemic (Saha et al., 2020). Many of the reductions in travel, especially early in the pandemic, were due to reduced social leisure activities as well as growth of teleworking of up to 80% (Irawan et al., 2020). The shift to remote work also shifted some modes, like walking, from primarily a productive mode to a leisure mode, as Jiao and Azimian (2021) found in Houston since April 2020.

The pandemic has also shifted travel patterns across modes due to changing destinations. Patterns of bike use have changed as they are beginning to be used more for leisure than for commuting. Chai et al. (2021) found that in Beijing there had been a sharp decline in bike-sharing use for productive purposes, especially near subway stations where they are often used for first and last mile service. Teixeira and Lopes reported similar findings in the first weeks of the pandemic in New York City, where bike-sharing use fell more inside the subway catchment than outside it (Teixeira & Lopes, 2020). Other use of bike-sharing has grown significantly; however, with increasing use of bike-sharing in New York City for causal users as well as increasing trip length) (Wang & Noland, 2021).

4.5.3 Pandemic's Impact on Different Demographic Groups

The impact of the COVID-19 pandemic on travel was not equal across geography or for different groups of people, often exacerbating existing patterns of inequality. Those in high-income jobs often had more opportunities for remote work which helped reduce their chance of infection while many working-class jobs are considered essential and cannot be moved online. Sy et al. found that areas with the highest median income had the greatest decrease in mobility during the pandemic and these were also the groups with the highest rate of COVID testing and a lower rate of positive cases (Sy et al., 2020). Similarly, Tirachini and Cats (2020) found that those with the ability to reduce their use of public transit largely did so, while those who continued to ride were those with no other transit options.

Education, gender, race, and age also play a significant role in shaping pandemic travel habits. Irawan et al. found that young people are more likely to undertake in-person leisure activities during the pandemic (Irawan et al., 2020). Dingil and Esztergár-Kiss (2021) also found that young people are more likely to choose bikes than cars, as do more educated groups. Finally, Jiao and Azimian (2021) found that men, white people, and those with graduate degrees are all less likely than others to reduce the number of trips that they take to the grocery store during the pandemic. These more privileged groups often have more access to private vehicles and often maintain higher levels of mobility while using less public transportation.

Those with additional vulnerabilities often experienced even more hardship from the mobility reductions brought on by the COVID-19 pandemic. Mogaji (2020) demonstrated that those in developing countries have seen a higher impact from travel restrictions since these countries often have larger informal economies that rely more heavily on in-person transactions. In this context, travel restrictions do more to disrupt economic, as well as social and religious activities. Changes in public transit have also had a larger impact on the elderly and those with disabilities, people who already had fewer transit options before the pandemic. Strategies like rear door boarding are not options for those in wheelchairs, making it harder for those with disabilities to continue riding transit. Communication issues in public transit systems also make it hard for many to know if or how transit services are still operating (Cochran, 2020).

4.5.4 Post-Lockdown Preferences

As restrictions continue to loosen and vaccinations become more widespread, we can expect that travel patterns will continue to change in response to these new conditions, as will responses of different transit authorities. Strategies to increase transit ridership under post-pandemic conditions are already being adopted with varying levels of success. Dai et al. showed that some fare-free policies that have been tried in China were effective at initially increasing ridership for subway systems, but that they had a limited long-term impact (Dai et al., 2021). Gkiotsalitis (2021) suggested a model of skipping bus stops to account for reduced capacity, determining that the resulting passenger load was decreased but that the model was only effective in areas with low demand. Many other cities have begun to encourage increased travel and access to businesses by adopting full or partial lane closures to allow for increased walking and biking space as businesses reopen (Combs & Pardo, 2021). Each of these methods offers additional ways to encourage increased transit as cities reopen and more normal activities resume.

During the pandemic, Abdullah et al. (2020) found that infection-related fears have become a primary factor in mode choice, replacing traditional reasons like time savings, costs, and comfort (Abdullah et al., 2020). But these changes are not likely to last as restrictions are lifted and the impacts of the pandemic lessen. In Spain, a survey was conducted to gage post-lockdown shared transit patterns. The survey shows that 89.7% of people will return to public transit, 67.7% of people will return to shared bikes and shared kick scooters, and 66.4% of people will return to taxis or ride-hailing services (Awad-Núñez et al., 2021). These people did expect new sanitation standards with transformative transportation and 64.3% of people even stated that they would pay extra for a ride to ensure health safety. In Germany, a user's perception of physical risk decreases when a covid safe claim is present (Garaus & Garaus, 2021). In the future, the most important criteria for transformative transportation will be social, economic, and environmental (Shokouhyar et al., 2021). Many services, both in and outside of transportation, endured a lot from the pandemic. Several practices that came about from the pandemic are likely to stay, while others many are excited to do without. It is imperative that the transportation field takes note of all these changes—both the changes that were forced as well as the changes that came about naturally or unintentionally. Acknowledging the transformations that COVID-19 has made to people's travel behavior as well as their general behavior (e.g., newfound hobbies, newfound methods of carrying out work) will help the transportation industry to best serve today's world.

4.6 Chapter Summary

A thorough literature review of both peer-reviewed and non-peer-reviewed sources provided great insight on the impact of COVID-19 on the transportation system. The review period spanned from the beginning of the pandemic until the summer of 2021. During this period, the status quo on COVID-19 was constantly changing due to major events such as confinements, stay-at-home orders, reopening, vaccine administration, etc. Hence, three chronological stages were identified to give context about how transportation has fared during this period—beginning, middle, and final stage. In the beginning stage of the pandemic, both traditional and transformative transportation modes endured enormous shifts in use and operation. By the middle of the pandemic, many transportation modes adapted back to a "new normal" and some trip types increased sharply such as shopping and transit trips. In the final stage, travel trends and operations increased back to their pre-pandemic equivalents.

Additionally, COVID-19's impact on transportation was not uniform. The pandemic had unequal effects across different demographic groups. Furthermore, several mode choices were affected more than others. For instance, transit and other transformative transportation services were impacted more than private vehicles. Trip purposes also changed tremendously during COVID-19. This was facilitated by the emergence of teleworking and other grocery delivery services. Finally, while a big part of the population yearns to go back to normal after COVID-19 is over, most of them are still skeptical and expressed caution regarding post-lockdown preferences.

5. UNDERSTANDING TRAVEL BEHAVIORS WITH REGARDS TO TRANSFORMATIVE TECHNOLOGIES IN SELECT INDIANA CITIES

Transformative micro-mobility modes, such as shared bike and shared e-scooter services, tend to track trip start and end time, trip origins and destinations, and other trip-related metrics. Often these micro-mobility companies publish these statistics on their websites, sometimes even providing the raw data from which those statistics are derived as downloadable files. These metrics have not been tracked as thoroughly for more traditional modes such as public transit and private vehicles, so it is good that these transformative transportation modes have recognized the value in such data. However, the most popular metrics being tracked by shared bike and shared e-scooter companies describe the characteristics of the trips being made with their fleet. Information about the users of these services, particularly information pertaining to the users' preferences, behaviors, and demographics, are not tracked or made available.

Understanding which demographic groups are using transformative transportation modes, as well as understanding why they are using these modes, is critical to predicting how these transformative modes will affect traditional transportation modes. For instance, if a significant fraction of transit users begins making their trips via shared e-scooters, this could imply/suggest changes were made to certain bus routes or the distances between certain bus stops. On the other hand, if the introduction of shared e-scooters in a city resulted in an uptake in transit ridership, this could mean that both modes not only can coexist, but also complement each other. To discover the motivations, preferences, and behaviors held by users of transformative transportation services, we constructed and electronically distributed two surveys for the Greater Lafayette residents and Indianapolis residents to take.

5.1 Bike-Sharing and Shared E-Scooter Demand in Greater Lafayette

The Greater Lafayette Area can be considered a "college town" in Indiana. This area is of interest because of its relatively low building and population density, especially when the summer months arrive, and classes are not in session. Bike-sharing use and shared e-scooter use have been studied and analyzed in more well-known, metropolitan areas that often have well-established transit systems and robust infrastructure. While the Greater Lafayette Area is not entirely lacking these features, its features are not as extensive. For instance, Greater Lafayette's CityBus transit system only includes buses and paratransit vehicles, while subways and passenger rails may constitute transit systems in larger cities. Also, CityBus' fleet does not have ridership rates as high as those of other transit agencies. For these reasons, it is necessary to obtain insight into the preferences, behaviors, and demographics of shared bike users and shared e-scooter users in the Greater Lafayette Area. The Greater Lafayette survey garnered a total of 1,124 responses. Many of these responses were from students who attend Purdue University, which is in West Lafayette, IN.

5.1.1 Greater Lafayette Survey Design

The survey instrument included the following four sections: (1) general travel behavior, (2) e-scooter usage, (3) bike-sharing usage, and (4) socio-demographic questions. Each section is further discussed in the following subsections. The general block asks the respondents whether they have used either shared e-scooters or shared bikes within the past year. If they select *shared e-scooter*, they are then sent to the shared e-scooter question block and bypass the shared bike question block. Similarly, if they select *shared bike* they are taken to the shared bike block and forgo the shared e-scooter block. If they select *none*, they are asked about their reasons for not using those micro-mobility modes. If they select *both*, they are asked which of the two they use more frequently and then sent to the block that corresponds with whichever mode they indicated using most often.

Overall, the survey consisted of several question types. Multiple choice answers were widely used across all sections along with some rank order questions. These question formats are considered among the easiest for participants to understand and answer. The language of the questions was intended to be concise and straightforward. Additionally, both the U.S. Census Bureau (2019) and the National Household Travel Survey (NHTS) were consulted to design questions and phrase the corresponding answers, especially for socio-demographic questions.

5.1.1.1 General travel behavior. This section consisted of preliminary questions that screened respondents. Participants were asked about the available transportation modes for their daily trips. Respondents then had to answer a screening question about whether they had used one or both shared e-scooter and shared bike services before. The survey would then proceed based on their answer to this question. It would end for those who have never used either service or would proceed to the related survey section based on the selected service. For instance, if they had answered that they have never used bike-sharing before, the bike-sharing section wouldn't be shown to them.

5.1.1.2 Shared e-scooter usage. This section focused on the usage habits and user preferences of the shared e-scooter service. Questions considered many topics that are further discussed in the subsequent subsections.

5.1.1.2.1 Shared e-scooter and other transportation modes. Questions pertaining to this topic focused on the usage of and opinion on other existing services in the system. Participants were asked about the reasons why they chose shared e-scooters over bike-sharing. Another question assessed why users chose this service over other modes. Additionally, participants were asked whether they use shared e-scooters to access the bus and whether they use an additional mode to access shared e-scooters.

5.1.1.2.2 Trip characteristics. This group of questions asked for details about the shared e-scooter trips. Two questions were sought for trip distance and frequency. Additionally, in one of the questions, participants were asked to rank the top three trip purposes for which shared e-scooter is usually used. Two other questions discussed the characteristics of the last e-scooter trip. Respondents were asked about the distance of the last trip in miles and about the last time they rode an e-scooter.

5.1.1.2.3 Willingness to ride. Participants' willingness to ride an e-scooter was addressed. One question asked about the maximum amount of money the users are willing to pay for an e-scooter trip. Another question solicited respondents' willingness to walk to access a vacant e-scooter to ride. In addition, a hypothetical question asked whether participants were willing, for one dollar in return, to leave e-scooters at a designated place that will increase their walking distance to/from their final destination.

5.1.1.2.4 Opinion about the service. The last question in this section assessed riders' opinions about certain attributes of the service. Participants were asked about what they would change the most about shared e-scooters and were given a set of choices such as the number of available units, price, dedicated lane, etc. This question also included *other* as an open-ended option to allow respondents to give other recommendations.

5.1.1.3 Bike-sharing usage. This section had the same format as the thoroughly discussed "shared e-scooter usage" section above (Chapter 5.1.1.2). It consisted of the same questions since the main aim of the survey was to investigate the usage characteristics of the two services. This format can also help uncover the differences and similarities between the two.

5.1.1.4 Socio-demographic information. This section asked for socio-demographic information. Participants were asked about their age, gender, educational attainment, and income levels. Also, information about the private car ownership and the average daily trip was sought after.

5.1.2 Survey Sample and Results

Shared e-scooters and shared bikes were introduced to the Greater Lafayette community in 2018. The survey was designed to obtain a complete picture of users because there was previously only aggregated data available. Survey responses were collected from January 2020 through August 2020. The survey data are used as input for the agent-based model to study how shared bikes and shared e-scooters could affect the current transportation landscape.

The COVID-19 pandemic unexpectedly interrupted the dataset. To combat this, pivotal dates were determined to compare the results before and after the pandemic. March 1, 2020 was the date used for shared e-scooters because that was the date when they returned to Purdue University's main campus. June 1, 2020, was the date used for shared bikes because that was the date when they were removed from the city of Bloomington, IN. Bloomington is also home to Indiana University which had a partnership with the Pace bikes before they were removed.

The demographics of both the shared e-scooter and shared bike portions of the data were similar. Table 5.1 shows the demographic attributes of the population. Participants were mostly female car owners under the age of 25 who were either pursuing or earned a bachelor's/associate's degree. Demographic details are shown in Table 5.1. Additionally, a summary table with all questions and their corresponding answers is found in Appendix B.

One question asked was about the reason shared e-scooter or shared bikes were chosen as a mode. Before the pandemic, most participants answered that they had used e-scooters because they wanted to try it out once, but this reason decreased in percentage during the pandemic. This change was also seen in shared bikes. The decrease in users wanting to test out e-scooters may be because e-scooters had been present for long enough that most people had already tried them out. During the pandemic, reasons like eco-consciousness and usability increased for e-scooters as seen in Figure 5.1. For shared bikes, users chose to save money more during the pandemic as seen in Figure 5.2, which could be explained by the financial strain faced at that time.

From the perspective of trip purposes, for both e-scooters and shared bikes, the three most popular trip purposes remained the same during the pandemic as depicted in Figure 5.3 and Figure 5.4. For e-scooters, the top trips are commuting to/from work/school, getting around campus, and social/entertainment. For shared bikes, the top trips are commuting to/from work/school, social/entertainment, and getting around

TABLE 5.1
West Lafayette survey demographics

Demographic	Definition	Number of Responses	Frequency (%)
Gender	Male	236	38
	Female	377	61
	Other	4	1
Age	Under 18	7	1
	18–25	338	55
	26-35	178	29
	36-45	71	12
	46-60	19	3
	61 and above	2	0
Income	I currently have no income	134	22
	$1–$20,000	164	27
	$20,001–$40,000	120	20
	$40,001–$60,000	82	13
	$60,001–$80,000	73	12
	$80,001–$100,000	27	4
	More than $100,000	15	2
Education	High school diploma/GED	46	7
	Associate's	35	6
	Bachelor's	341	55
	Masters	97	16
	Doctorate	56	9
	Other	8	1
	Blank	32	5
Car Ownership	Yes	371	60
	No	244	40
Micro-Mobility Usage	Shared e-scooters	213	35
	Shared bikes	159	26
	Both	243	40
COVID-19	Pre	178	29
	Post	437	71

campus. The consistency in these responses shows that these trip types may become more popular for bike-sharing and e-scooters use.

When asked about the time of the last shared bike trip, there was an increase in use during the pandemic for both modes. E-scooter and shared bike trips within the last month increased by 27% and 32%, respectively, during the pandemic (Figure 5.5 and Figure 5.6). This increase in e-scooter trips can be attributed to the perception that e-scooters were a safer mode of transportation at the height of the pandemic. However, the shared bike trip increase is unlikely to represent their use of the system in Greater Lafayette due to the bikes being permanently removed. This shows that the survey might have been affected by students returning to their hometowns and therefore using their hometown's modes to answer the survey.

The survey also asked what alternative modes users would have taken if e-scooters or shared bikes were not available. Both e-scooter and shared bikes saw a large percentage decrease in walking, which takes up most responses. Metro rail, Uber/Lyft, and personal vehicles increased in both modes as seen in Figure 5.7 and Figure 5.8. The metro rail may again be explained by students returning to their hometowns. Shared and personal vehicles may have increased due to safety concerns. This result shows that shared micro-mobility services have been increasingly used to replace non-walking modes due to the pandemic.

5.2 Demand for Transformative Transportation Technologies in Indianapolis

Transformative technologies, including bike-sharing, ride-hailing, and e-scooter-sharing are now crucial constituents of the transportation system. For more than a decade, these transformative transportation services have been scrutinized to help maintain regulations and keep updating the transportation system. In addition, cities have dealt with these transformative technologies differently when it comes to policies enactment. This dictates dealing with each instance on a case-by-case basis which necessitates developing a different survey for Indianapolis.

Data for these studies have been mainly acquired using different means. A commonly used collection method is survey taking. This data relies on stated preferences and offers substantial information on the

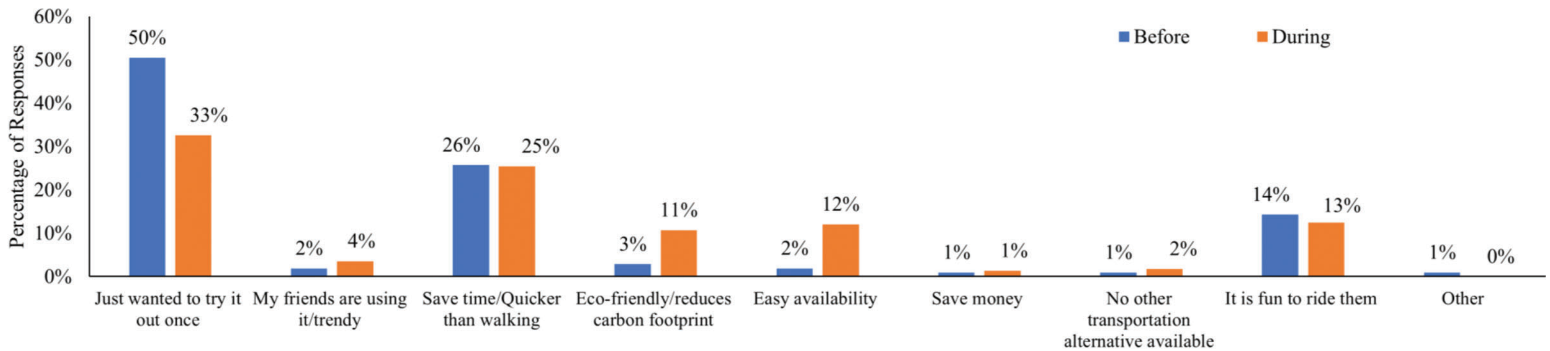


Figure 5.1 The primary reason for choosing shared e-scooters over other modes of transportation.

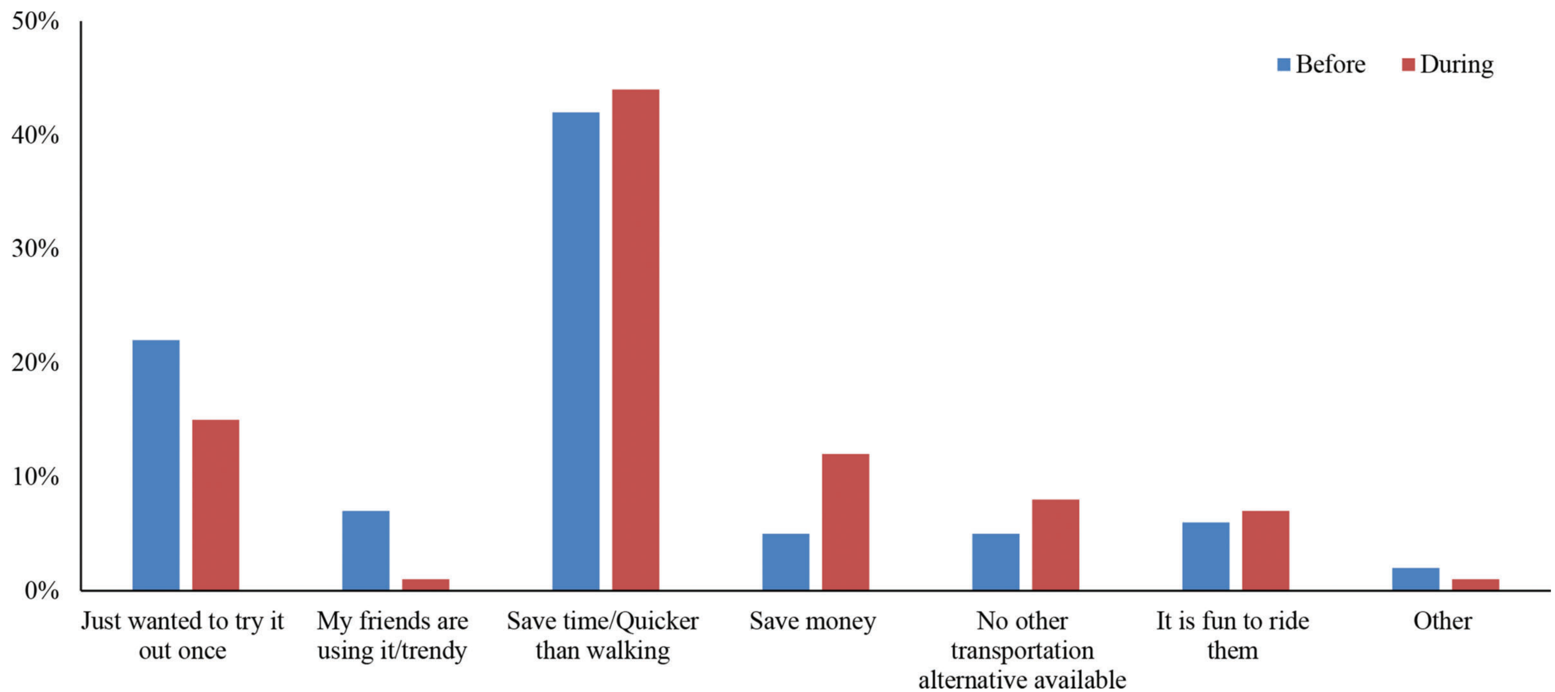


Figure 5.2 The primary reason for choosing shared bikes over other modes of transportation.

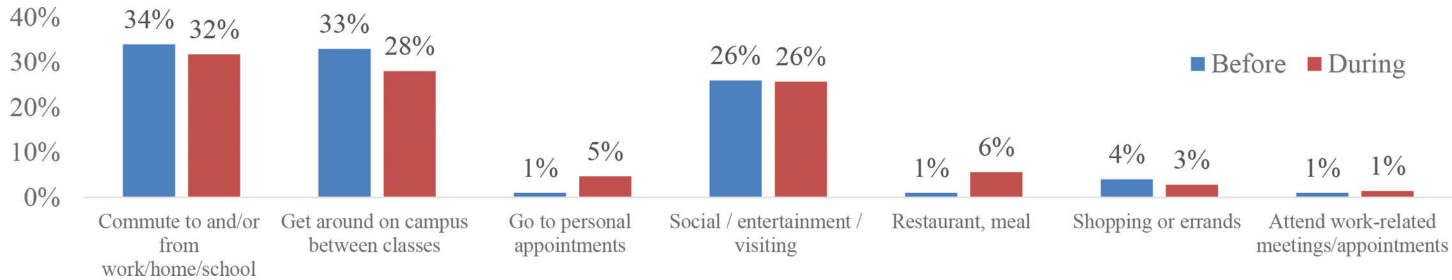


Figure 5.3 Top shared e-scooter trip type.

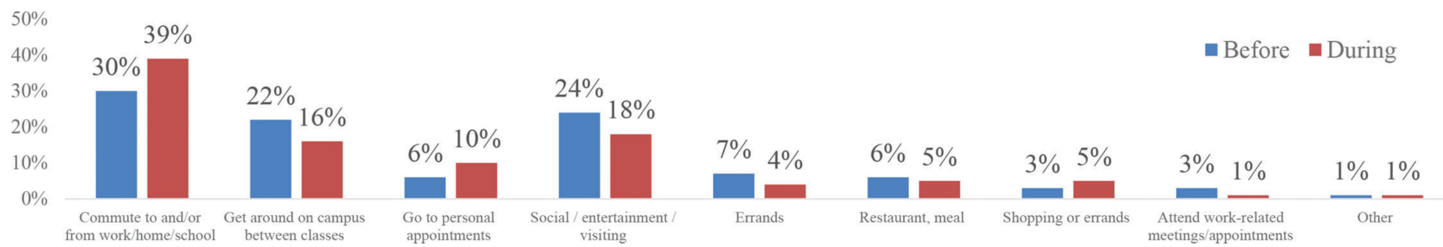


Figure 5.4 Top bike-sharing trip type.

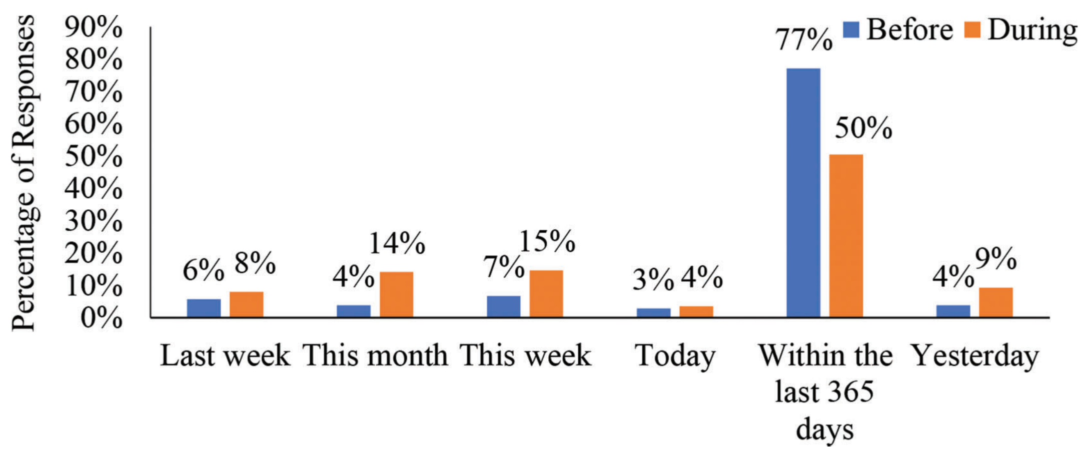


Figure 5.5 Time of last shared e-scooter trip.

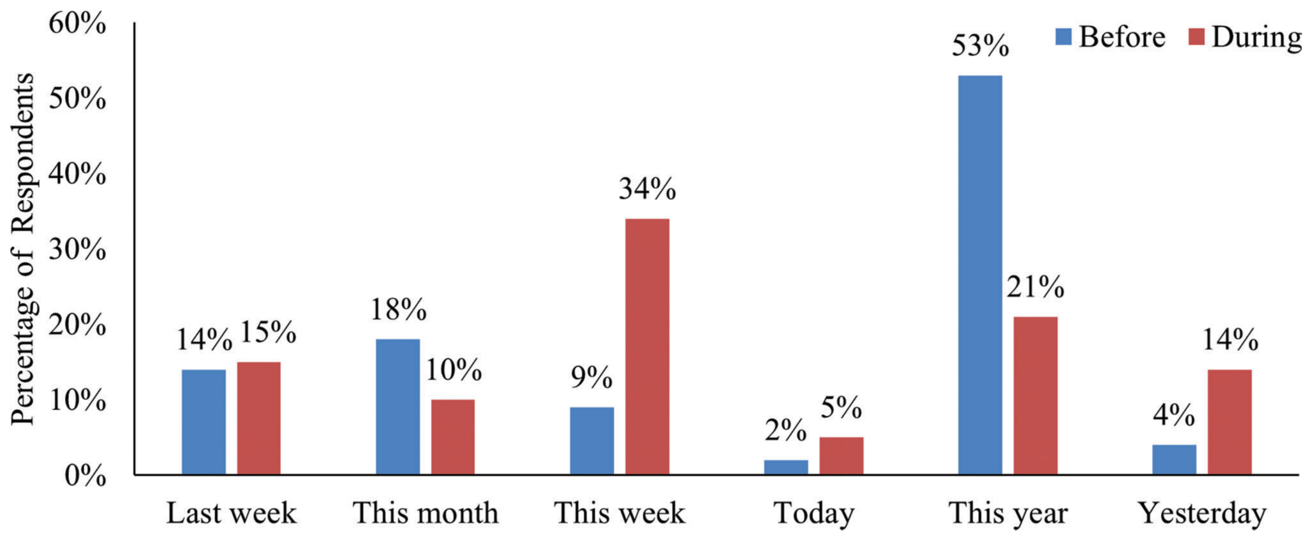


Figure 5.6 Top bike-sharing trip type.

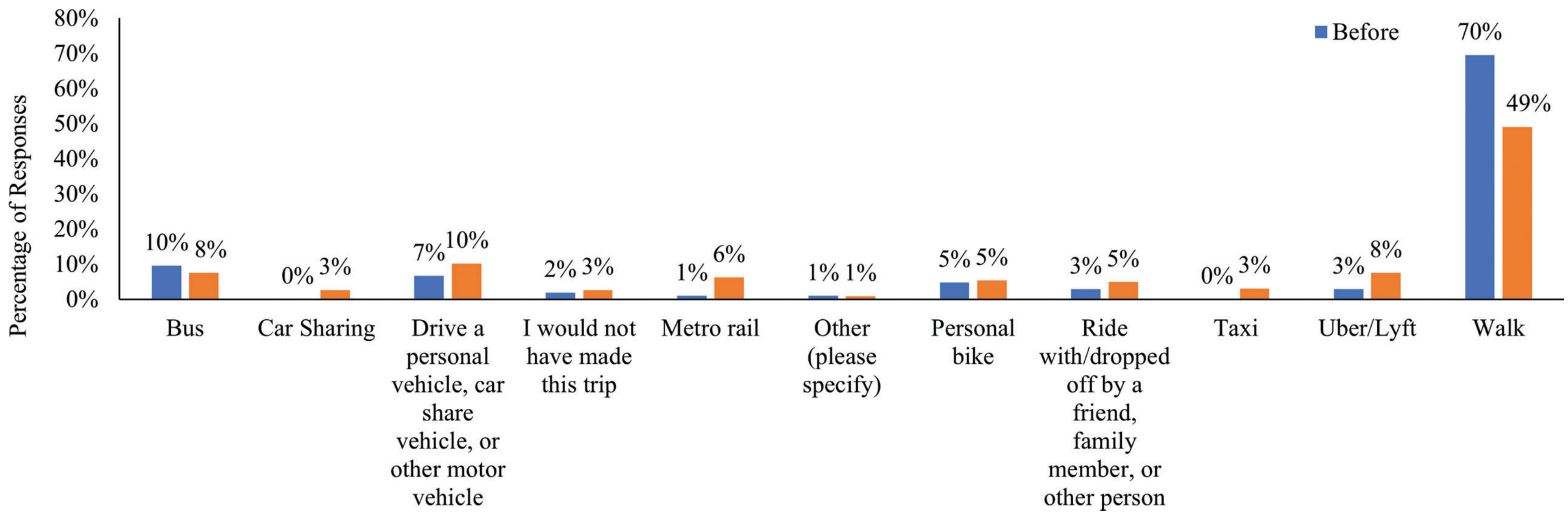


Figure 5.7 Alternative travel mode taken if shared e-scooters were not available.

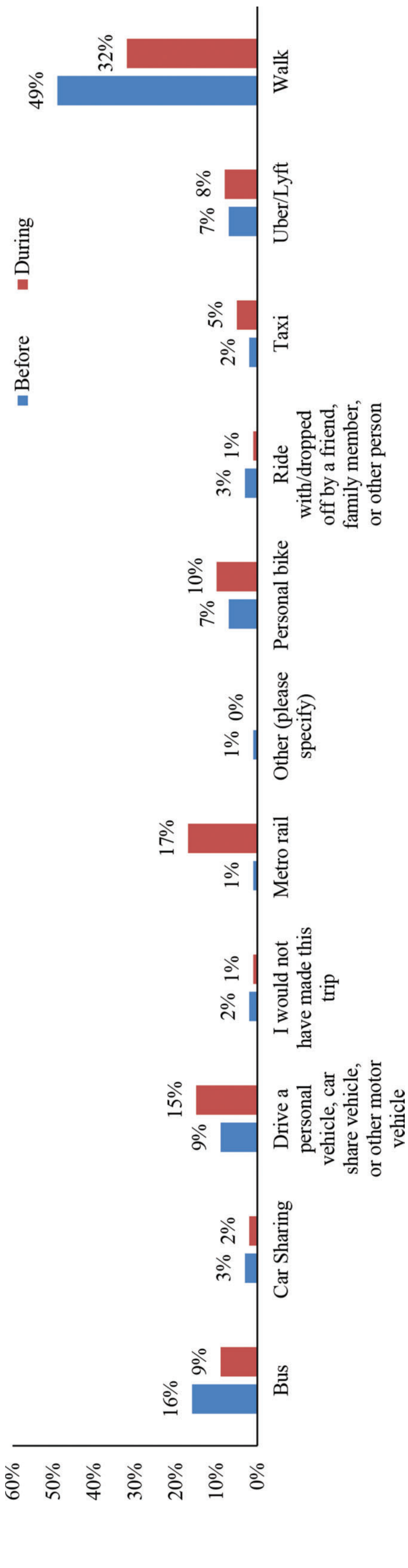


Figure 5.8 Alternative mode taken if the shared bikes were not available.

demographics of the users. Thus, given that previous questionnaires were of the essence to collect data related to transformative transportation, existing literature was consulted to develop our survey instruments. Two main aggregate sources were transportation agencies and transformative transportation studies. Questions from these sources were exploited based on the relevance of the data.

5.2.1 Indianapolis Survey Design

The Indianapolis survey was developed to include six sections. Each section was designed to capture a certain travel behavior in the population. While the first section, for example, aimed at investigating the general behavior related to the respondent's frequency of travel, the second and third sections were more about capturing the population's habits regarding transformative transportation technology and multimodality, respectively. Listed below are the sections of the Indianapolis survey which are discussed further in due course.

1. General travel behavior
2. Shared-mobility use
   a. Bike-sharing
   b. E-scooter-sharing
   c. Ride-hailing
3. Multimodality
4. Choice experiment
5. Users' perception of transformative transportation technology
6. Socio-demographics section

Different types of questions were included and utilized in this survey. Matrix tables were commonly used especially in the first two sections. Known as one of the most popular question types, a matrix question is both easy to program from the creator's side and to interpret (and hence answer) from the respondents' side given that answer options and scales stay the same across all table items. However, the number of these tables was carefully handled to make sure that it's not being overused because answering multiple tables can easily lead to respondents' fatigue and yield poor survey results. Multiple choice and five-point Likert scales were also used across the survey, especially in the choice experiment which had three choices per question. Throughout the survey, some questions were presented twice to account for pre and post COVID-19 conditions. Additionally, concise and understandable language was maintained across the survey instrument to avoid ambiguity and ensure good survey-taking behavior. Similar to the Greater Lafayette survey, both the U.S. Census and the National Household Travel Survey (NHTS) were consulted to make sure that the format of socio-demographic questions conforms with the existing convention.

5.2.1.1 General travel behavior. The aim behind this section was to understand the frequency of usage of each mode and be able to compare them. Questions in this section focused on travel behavior in general. They did not focus on any specific transportation mode, instead, they addressed daily decisions taken with regard to mode preference, route choice, departure time habits, etc. Numerous questions pertaining to general transportation topics such as trip purpose and frequency of trip were recurring in almost all reviewed surveys (Baltimore City Department of Transportation, 2019; Orr et al., 2019). Participants were asked about trip frequency, the travel mode used for certain trip purposes, and connectivity to the bus. Each question was asked twice considering pre and post COVID-19 conditions using the table matrix format. Other questions evaluated vehicle ownership using multiple-choice questions. And finally, a Likert scale was used to ask about the importance of certain attributes, such as cost, travel time, waiting time, reliability, comfort, etc., when choosing a transportation mode.

5.2.1.2 Shared-mobility use. This section sought to understand how the usage of transformative transportation impacts mobility in the city and the usage of other modes. Hence, several surveys of transformative transportation pilot programs were consulted (Baltimore City Department of Transportation, 2019). The section started with a screening question that asked about the use of each of the following services: bike-sharing, e-scooter-sharing, and ride-hailing. After that, this section was split into three similar subsections representing three transformative transportation services. Participants were shown the following subsections based on their usage history of the services (i.e., a respondent who had never used bike-sharing before would not be asked to fill out bike-sharing-related questions).

5.2.1.2.1 Bike-sharing/shared e-scooter/ride-hailing. The first question asked about the reduction in the number of automobiles ownership as a result of the introduction of transformative transportation services. Then participants had to answer a series of multiple-choice questions regarding transformative transportation technology trip characteristics such as time of the last trip, primary mode, and specific trip purposes for which this service was used. Two other questions addressed the effect of transformative transportation technology on the usage frequency of other modes and discussed the service's unavailability. This section ended with a five-point Likert scale COVID-19 question asking participants whether they feel safe using the service.

These questions were repeated for each shared-mobility service. This format can help compare these modes and understand the different characteristics pertaining to each.

5.2.1.3 Multimodality. The main purpose of this section was to discuss connections, first/last mile trips, and multimodal trips. Several surveys were reviewed for relevant questions such as (Shaheen et al., 2014) which helped expand questions related to the impact of bike-sharing on transit in our survey. Respondents were asked whether they made transfers to complete their trips and then those who answered yes were additionally asked about the trip destinations for which these transfers were made. Following that, three questions were asked about the use of transformative transportation technology for the first/last mile purposes and specifically to access the bus. Also, the effect of COVID-19 on the first/last mile trips was monitored by duplicating each question to account for the pre and post COVID-19 conditions.

5.2.1.4 Choice experiment. The aim of this model is to help us determine the mode with the maximum utility which allows us to update the agent-based model. The choice experiment examines the impact of certain attributes such as time and cost on respondents' preferred transportation mode. Time and cost were exclusively used to avoid complexities in our model, and since they arguably influence people's mode choice the most compared to other attributes. Several previous studies have utilized state preferences when it is inconvenient or not possible to collect revealed preferences. Please refer to Table B.1 in Appendix B, which includes multiple reviewed studies that have used choice experiments for applications relevant to our study.

The survey included two different choice experiments. While both followed the same design recommendations, each tackled a different scenario. Each scenario began with a cheap talk, then participants were shown a base scenario question that offered different mode choices reflecting their revealed preferences. The question was followed by a set of eight questions offering more mode choices and eventually asking about the respondents' stated preferences.

Both choice experiments were designed following a blocked fractional factorial design (Resolution IV) to reduce the number of questions shown for each respondent and ensure good data quality (Hensher et al., 2005).

Additionally, one important consideration was the extent that choice experiments (stated preferences) can translate to real-life settings (revealed preferences). This issue is called hypothetical bias, and when present, it generally results in biased results. Plenty of research has been going to understand and find solutions for the effect of hypothetical bias on results. A review study by Haghani et al. (2021) listed several choice experiment transportation studies that have significant degrees of unmitigated hypothetical bias. Hensher et al. (2005) mentioned to use a cheap talk script before presenting the choice experiment questions as a remedy for hypothetical bias in the survey. This script basically puts the story in context for the respondents and helps them imagine the scenarios. Other studies in the literature have proven cheap talks to be very effective when mitigating the effect of hypothetical bias (Cummings et al., 1995; List et al., 2006). Cheap talks can be implemented using various effective techniques such as oath-taking (Jacquemet et al., 2013), discussing respondents' exaggeration in advance and telling them about hypothetical bias (Brown et al., 2003).

Each attribute was carefully selected and calculated to reflect the actual numbers pertaining to the existing modes. The corresponding sources behind the rationale are presented in Table 5.2.

5.2.1.4.1 Choice experiment 1: recreational. The first choice experiment addresses the recreational aspect of transformative transportation technology use. Participants were asked to imagine that they work in downtown Indianapolis, 1 mile away from the canal. They would make a midday recurring trip to the canal to have lunch there and come back. The base scenario question offered them three modes which were private car (depending on whether they have one), public transit, and walking.

After answering the base scenario questions, they were then shown eight questions that offered the following four options: their previously picked base scenario option, shared e-scooter, bike-sharing, and ride-hailing.

Each mode choice had a list of attributes that had two levels (high and low). The attributes for the base scenario modes and the transformative transportation modes are shown in Table 5.3 and Table 5.4, respectively.

5.2.1.4.2 Choice experiment 2: commuting. The second choice experiment shed light on the possibility of using transformative transportation technology for commuting purposes as well as a first/last mile mode. This time, participants were asked to imagine that they lived in the suburbs of Indianapolis and that they commute every day for 6 miles to reach their workplace in downtown Indianapolis. They were also offered the following three modes in the base scenario: private vehicle, walking to take the bus to work, and ride-hailing to work.

Eight questions followed this base scenario offering them the following four options: the mode that they picked in the base scenario, using shared e-scooter

TABLE 5.2
The data sources behind the attributes in the choice experiment

Mode/Attribute	Cost (in U.S. dollars)	In-Vehicle Time (in minutes)	Out-of-Vehicle Time (in minutes)
Private Vehicle	Fuel cost from AAA (2019); Parking cost from Downtown Indy (2021)	Google Maps API	Street search from INRIX (2017); Time to access the car is an assumption
Walking	NA	Knoblauch et al. (1996)	NA
Public Transit	Bus fare in 2021 from IndyGo (IndyGo, n.d.)	Google Maps API	Google Maps API
Shared E-Scooter	E-scooter fare from Lime, Bird, and Spin	Average e-scooter speed in downtown Indy (City of Indianapolis and Marion County, 2022)	Assumption based on logical walking time values
Bike-Sharing	Indiana Pacers (bike-sharing company)	Based on NACTO (2018)	Google Maps API
Ride-Hailing	Ride-hailing fare from Uber (2020)	Google Maps API	Average wait time from Smith (2019) and Google Maps API

TABLE 5.3
Attributes values for the base scenario in the first choice experiment

Attribute/Mode	Private Vehicle	Public Transit	Walking
Cost (in U.S. dollars)	2	1.75	0
In-Vehicle Time (minutes)	5	15	23
Out-of-Vehicle Time (minutes)	7	4	0

TABLE 5.4
Attributes values for the alternative scenarios in the first choice experiment

Attribute/Mode	E-Scooter-Sharing		Bike-Sharing		Ride-Hailing	
Level	Low	High	Low	High	Low	High
Cost (in U.S. dollars)	3.8	5.2	3.4	4	8	14
In-Vehicle Time (minutes)	7	15	16	20	4	7
Out-of-Vehicle Time (minutes)	2	4	4	6	8	10

along with the bus to make the trip, using bike-sharing along with the bus to make the trip, and using ride-hailing along with the bus to make the trip. These modes were chosen to get insight into the use of transformative transportation technology as a first/last mile mode to connect to the bus.

Attributes' allocation was no different from the previous choice experiment. Each mode choice had three attributes which are cost, in-vehicle time, and out-of-vehicle time. Each attribute had two levels (high and low). The attributes for the base scenario modes and the transformative transportation modes are shown in Table 5.5 and Table 5.6, respectively.

5.2.1.5 Users' perception of transformative transportation technology. With the aim to understand the opinions of residents regarding transformative technologies, the section included questions related to user perceptions and preferences of different transformative transportation modes. Similar surveys included questions related to perceptions that inspired our choice of questions (City of Austin Transportation Department, 2019). Hence, three different sets of questions were asked to better understand the motivations and barriers of using transformative transportation services. The most frequent type of questions was multiple-choice except for one matrix table about COVID-19. All questions followed a five-point Likert scale because they are easier to answer and simpler to analyze. In the first set, respondents were asked to reveal their opinion about some conditions that might affect their usage of transformative transportation services such as weather, parking spots, connecting to the bus, etc. The second set of questions investigated reasons that would incentivize respondents to use transformative transportation services such as congestion, low cost, and designated infrastructure. The third section focused on reasons that might discourage respondents from using the services such as technology, long walks, probability of contracting COVID-19, etc.

5.2.1.6 Socio-demographic information. Participants were asked for socio-demographic information in this section. It consisted of questions about gender, age, employment status, income, educational attainment, race, and household size. A question was also asked about home address ZIP code to be able to identify their geographic location. Lastly, information about any disability was included.

5.2.2 Sampling Strategy, Data Collection, and Data Cleaning

5.2.2.1 Sampling strategy. The Indianapolis survey includes a mode choice experiment. To ensure that the model is robust and yields accurate results, the data needs to be extensive and varied. This needs to be accomplished by making sure that respondents have different travel habits. For instance, participants who mainly use private vehicles as their dominant transportation mode will likely select private vehicles in the choice experiment over other options. For that reason, we followed a procedure that ensured a variety of participants, with different transportation habits, were included in the sample.

5.2.2.1.1 Sampling distribution. Special care was taken when deciding on the sampling strategy. Stratified sampling was considered to reflect the variety of preferences of travelers and make sure that they are all represented, especially in the mode choice experiment.

A known general indicator of travel habits is the means of transportation to work. In this regard, the American Community Survey (ACS) includes a question about the commuting transportation mode. The modes listed under this question are the following.

- Private vehicles
- Public transit (bus)
- Taxicab
- Bicycles
- Walking
- Others

TABLE 5.5
Attributes values for the base scenario in the second choice experiment

Attribute/Mode	Private Vehicle	Walking to the Bus	Ride-Hailing
Cost (in U.S. dollars)	4.3	1.4	12
In-Vehicle Time (minutes)	14	22	14
Out-of-Vehicle Time (minutes)	3	21	7

TABLE 5.6
Attributes values for the alternative scenarios in the second choice experiment

Attribute/Mode	E-Scooter to Bus		Bike-Sharing to Bus		Ride-Hailing to Bus	
Level	Low	High	Low	High	Low	High
Cost (in U.S. dollars)	5.2	6.6	4	4.6	6.9	8.9
In-Vehicle Time (minutes)	29	37	38	42	26	29
Out-of-Vehicle Time (minutes)	2	4	4	6	8	10

The data collection results from the ACS survey indicate that the modal split in Indianapolis is highly skewed and that most people (over 90%) use cars whereas less than 1.5% use public transportation.

Given that the number of users of other modes is low compared to cars, the sample's subgroups were clustered as follows.

- Private vehicles
- Buses
- Taxi, walking, and private bikes
- Transformative transportation technology

NHTS survey also contained a similar question regarding means of transportation and offered similar results regarding the modal split in Indianapolis.

5.2.2.1.2 Overall sample size. We aimed for a 95% confidence interval, a response distribution of 50% and a margin of error of 5%. Proper calculations indicated that a sample size of roughly 384 would be representative of the Indianapolis population. Finally, it was decided to collect a sample of at least 400 participants.

5.2.2.1.3 Sample size allocation. Normally, a proportional allocation would be used across the aforementioned transportation modes' subgroups. In this survey, this allocation method was not the best choice because of the constraints that the mode choice experiment posed.

The choice experiment and the pertaining utility function require that every subgroup be represented by a minimum number of respondents. For example, the proportional allocation would require bus users to be represented by 7 respondents from the 400 according to the modal split in the city. However, the choice experiment model would require, for example, a minimum number of participants who use the bus to yield accurate results.

To obtain the minimum number of participants in each subgroup is, several sources investigating relevant theories were explored. Although there were not any definitive answers regarding that, but a set of rules of thumb and equations had been established based on previous literature and experience in that regard (Ben-Akiva & Lerman, 1985; Hensher et al., 2005; Johnson & Orme, 2003; Louviere et al., 2010). Based on the literature, it was eventually decided that the minimum number of respondents in each subgroup should be 50.

5.2.2.1.4 Final sampling decision. Table 5.7 that lists the minimum number of respondents needed in each subgroup.

TABLE 5.7
Detailed sample size

Means of Transportation to Work	Our Sample	%
Private Vehicle Total	200	50
Bus Total	100	25
Walking + Bike + Taxicab Total	50	12.5
Transformative Technology Total	50	12.5
Total	*400*	*100*

5.2.2.2 Data collection and cleaning. The survey was distributed during the summer of 2021. Before data collection started, IRB approval was granted as well. The first response was collected on July 30th and the last one on October 7th. More than 2,400 responses were received but only around 420 participants completed the survey due to not meeting the screening criteria. Participants for the study were recruited through Dynata, a company providing global online market research services using the internet as a data collection platform. The subjects of this study were subscribed to their panel.

5.2.2.2.1 Data cleaning. Observations passed through many checks before making it to the final list of the clean dataset.

- Screening criteria. Participants who were under 18 or lived outside Marion County could not complete the survey.
- Survey total completion time—observations with a completion time of less than 1/3 of the median were removed.
- Attention checks/trap questions. Four attention checks were included in the survey. Participants who failed to pass these checks were directly removed. Table 5.8 shows the four checks.
- Quotas. After deciding what our sampling strategy was, a question was included at the beginning of the survey asking about the participants' primary mode. Quotas were assigned to each answer according to the sampling plan. For instance, when car users exceeded 200, we started pushing towards getting participants who use other modes.

5.2.2.3 Weighting. After cleaning the data, the data needs to be weighted to ensure representativeness because the collected sample was not proportional to the modal split in Indianapolis. It has been well established in the literature that usage of transformative transportation technology is dictated by a set of demographics which are mainly age, gender, and income. Hence, the following three demographic segments were used to adjust the weights of the observations after sampling.

An ACS table was generated with the same demographic brackets as our data. The geographic area of Marion County was selected. The data was weighted to match the population's demographics. For additional information, please refer to Table B.2.

Weighting a sample usually is accompanied by a decrease in precision due to unequal weighting of the observations. To estimate that loss, the unequal

TABLE 5.8
Attention check questions

Q1	Now that the pandemic has come about, how often do you use each of these modes? For this option, please choose *a few times a month.*
Q2	In the following table, assuming post-COVID conditions apply, please indicate the level of importance that each attribute has when choosing a transportation mode for an average distance work trip? (An average distance work trip is defined as a commute that is less than 10 miles). For this option, please choose *extremely important*.
Q3	Since you started using ride-hailing do you find you use the following options more or less? For this option, please choose *less often.*
Q4	Please select *strongly disagree* as your answer choice.

TABLE 5.9
Demographics of the Indianapolis survey after weighting

Demographic	Value	Frequency	%
Gender	Male	194	46
	Female	226	54
Age	18–24	50	12
	25–34	92	22
	35–44	73	17
	45-54	68	16
	55–64	67	16
	65 and over	72	17
Income	Under $25,000	60	14
	$25,000–$49,999	111	26
	$50,000–$74,999	66	16
	$75,000-$99,999	66	16
	$100,000–$149,999	63	15
	$150,000 and over	34	8
	Prefer not to answer	23	5
Employment	Work full time	201	48
	Work part time	60	14
	Homemaker	19	4
	Student	22	5
	Currently unemployed	28	7
	Retired	75	18
	Other	17	4
Education	College graduate	232	55
	High school graduate	181	43
	Nursery or preschool through grade 12	4	1
	No schooling completed	6	1
Car Ownership	Yes	403	95
	No	21	5

weighting effect (UWE) was calculated using the following formula (Biemer & Christ, 2008).

$$\mathrm{UWE} = 1 + \frac{\mathrm{Var}(w_i)}{\bar{w}^2} = 1 + cv^2_{\mathrm{weights}} \qquad \text{(Equation 5.1)}$$

where w_i is the weight of individual i

cv^2_{weights} is the squared coefficient of variation of weights (standard deviation/mean).

A UWE of 1.49 was obtained. This indicates that the magnitude (multiple) that the variance of a mean will increase due to the weights is 1.49 (or 1.22 for the standard error of the mean). The low number indicates that not much precision is lost compared to the amount of representativeness gained. Table 5.9 shows the post weighting demographics of the survey.

5.2.3 Survey Results

5.2.3.1 Descriptive analysis. The survey extensively focuses on the impact of both transformative transportation technology and COVID-19 on the transportation system, travel habits, and preferences in the city of Indianapolis. Thus, the analysis section is grouped into two main subsections—transformative transportation technology and stated impact of

COVID-19. Please note that COVID-19 is still discussed in the transformative transportation technology section and vice versa.

5.2.3.1.1 Who uses transformative transportation technology? In this section, general demographics of transformative transportation technology users are presented to provide an overview of user profiles of transformative transportation technology services in the city.

Participants were asked whether they have used transformative transportation technology services before. Figure 5.9 shows that 16% (n = 67) of the participants stated that they have used bike-sharing before. Of the participants, 18% (n = 76) stated that they have used shared e-scooter before. Expectedly, much more people (62%, n = 263) said that they have used ride-hailing. Part of the reason that ride-hailing has higher adoption may be its longer history than the micro-mobility services.

Additionally, Figure 5.10 presents gender distribution of transformative transportation technology users. Two out of every three bike-sharing users were males. The gap was much smaller for the other two services. While the number of males who use e-scooters was slightly higher, the gap was very insignificant for ride-hailing users.

Most transformative transportation technology users pertained to the younger generation. Figure 5.11 shows that age distribution is skewed. More than 70% of bike-sharing users were young than 44 years old. E-scooter users were also on average younger than bike-sharing users with more than 80% of users under 44 years old. Ride-hailing was slightly more spread across the age brackets. Almost 40% of users were older than 45 years old.

Regarding income, most bike-sharing users belonged to the medium-to-high income brackets (80%) as shown in Figure 5.12. More than 43% of bike-sharing users earn more than $100,000. On the other hand, the trend is opposite for e-scooters and ride-hailing. The number of users decreased with the increased income. In other words, these services are used more by low-to-medium income users.

In the context of employment, Figure 5.13 shows that transformative transportation technology users were dominantly full-time workers. The other most well-represented category was part-time workers. However, ride-hailing users were more diverse. A big number of users were retired users which explains the good representation of old age brackets as well. This shows that the older generation uses ride-hailing as well for its convenience.

5.2.3.1.2 Shared-mobility and other modes. The survey also included questions to explore how transformative transportation technology is used in parallel with other modes. Hence, this section of the analysis seeks to understand how the emergence of transformative transportation technology affected the usage of other modes in the transportation system.

Participants were asked whether their usage of transformative transportation technology had affected

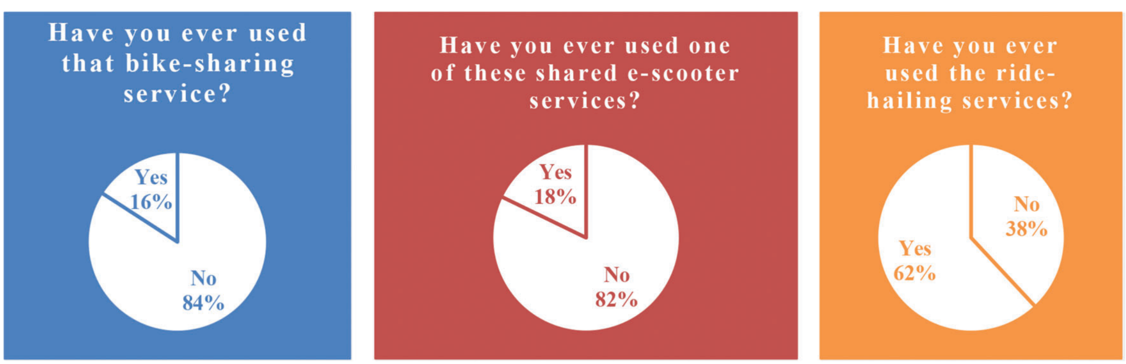


Figure 5.9 Percentages of transformative transportation technology service users in order from left to right: bike-sharing, shared e-scooter, and ride-hailing.

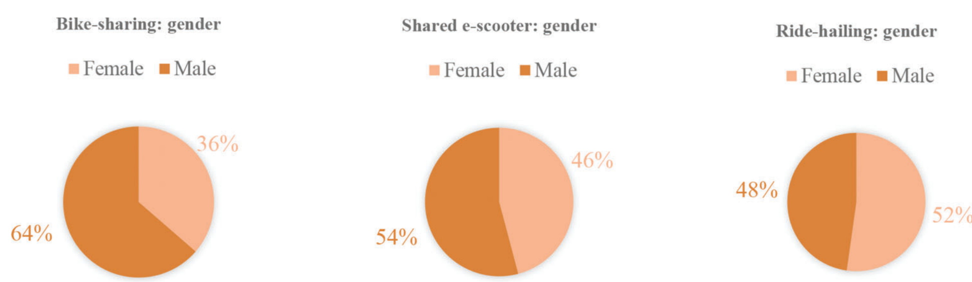


Figure 5.10 Gender of transformative transportation technology users from left to right: bike-sharing, shared e-scooter, and ride-hailing.

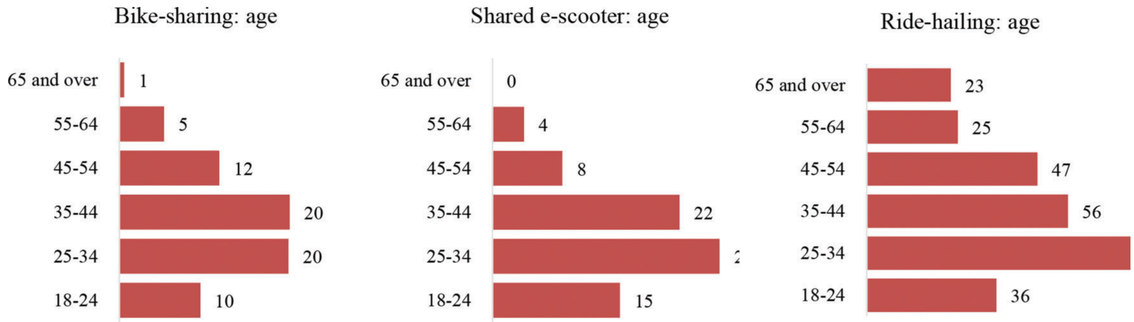


Figure 5.11 Age distribution of transformative transportation technology users from left to right: bike-sharing, shared e-scooter, and ride-hailing.

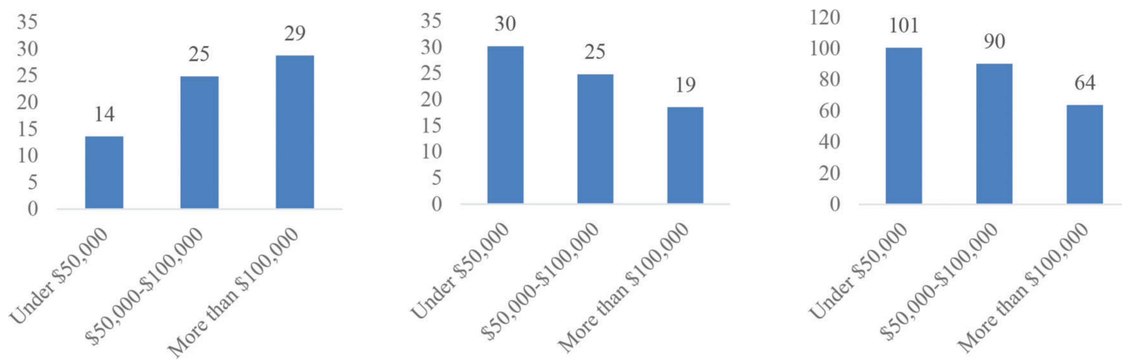


Figure 5.12 Income of transformative transportation technology users from left to right: bike-sharing, shared e-scooter, and ride-hailing.

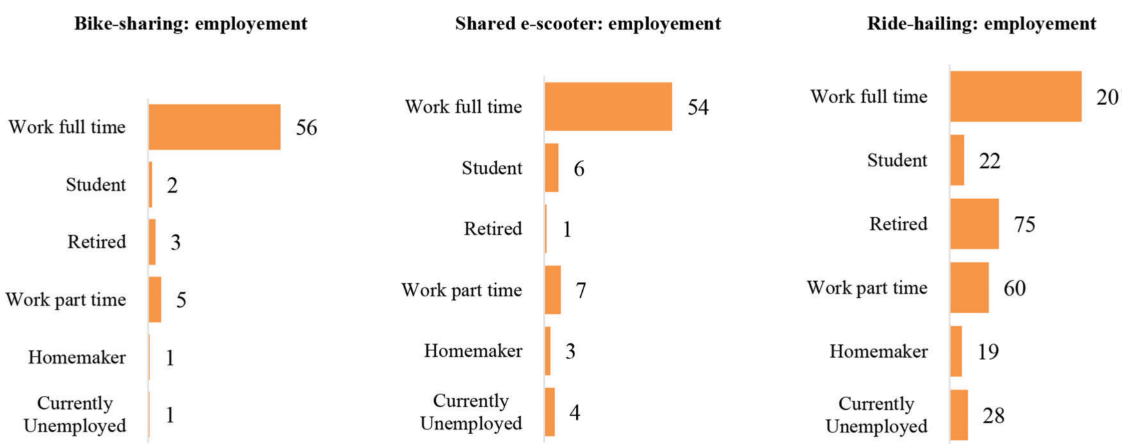


Figure 5.13 Employment status of transformative transportation technology users from left to right: bike-sharing, shared e-scooter, and ride-hailing.

their usage of other modes. The question asked to rate whether they are using any mode less, about the same, or more because of transformative transportation technology.

Figure 5.14 shows that the majority of users kept on walking and using their cars about the same. In other words, their usage of cars and walking wasn't much affected by the introduction of e-scooters. On the other hand, a good number of participants stated that they are using taxis and transit less often due to e-scooters' usage. This means that e-scooter is replacing the bus instead of complementing it.

The trend was quite similar for bike-sharing and ride-hailing (Figure B.1 and Figure B.2). Most users reported that they are still walking and using their cars about the same. Regarding the other modes (taxi, transit, and shared e-scooter), the majority stated that they are using them less often after starting to use the

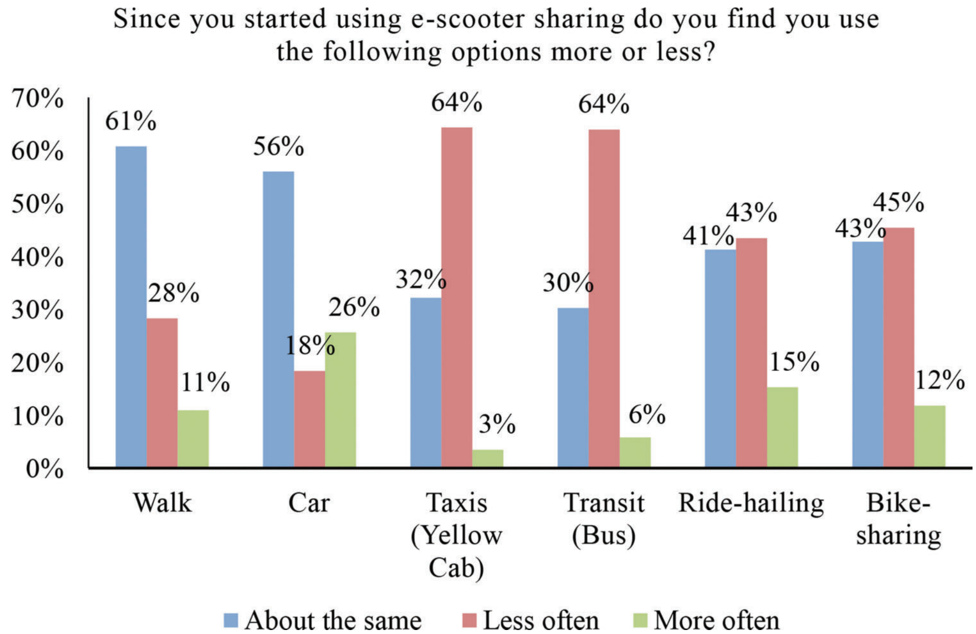


Figure 5.14 Usage of other modes after starting to use e-scooters.

services. These results show that bike-sharing, shared e-scooter, and ride-hailing can also be competing.

Plenty of studies explored the usage of transformative transportation technology as a solution for first mile/last mile (FMLM) trips. The survey included questions related to multimodal transportation trips and sought to understand how, if ever, transformative transportation technology is used to improve public transit use.

Participants were asked whether they usually make mode transfers to complete their trip. Figure 5.15 shows that only 20% of them do. Another question asked specifically about the usual mode used for FMLM. The majority of respondents stated that they depend on walking to complete their FMLM. Walking became even more prevalent after COVID-19 whereas the other modes, which were not as used even before, still witnessed a drop. This shows that walking is still the dominant solution for FMLM, and bike-sharing and e-scooters are still not as used.

Furthermore, participants who make mode transfers were asked about the modes they used for different trip purposes (see Figure 5.16). Active modes (which included walking, personal bikes, and personal scooters) were the most used modes for most multimodal work trips. Additionally, cars are the most used modes concurrently with other modes for all other multimodal trips. Buses are used in multimodal trips for work more than other purposes. Transformative transportation technology is decently used for social and family multimodal trips and is used more than buses for these trips.

Whether transformative transportation technology complements or competes with the bus has been an extensively asked question in the literature. There's still no consensus on an answer since the usage of transformative transportation technology highly depends on the transportation system that it's present. In this regard, the survey asked participants about how often they use transformative transportation technology to access the bus. Most participants stated that they never use transformative transportation technology to access the bus. There was a decent number of participants who reported connecting to the bus at least once per week. Figure 5.17 shows how most respondents do not use e-scooters to connect to the bus. The same question was asked of bike-sharing users. The results were almost similar to the ones for e-scooters.

A question asked participants about what they would use in the case of transformative transportation technology was unavailable for their last trip using transformative transportation technology. In the case of e-scooters, which is shown in Figure 5.18, the majority stated that they would have walked to complete their trip. Over 30% of people stated that they would use their cars. Others also stated that they would use ride-hailing. For bike-sharing trips, fewer people answered that walking would replace their trips. This shows that e-scooter trips are perceived as shorter than bike-sharing trips and can be more likely replaced by walking. On the other hand, participants mainly selected cars to be used in case ride-hailing was not available for their last trip. This shows that ride-hailing trips are most likely replacing car trips. The graphs for bike-sharing and ride-hailing are found in Appendix B (Figure B.3 and Figure B.4).

5.2.3.1.3 Perception of transformative transportation technology. Since transformative transportation technology is still not as prevalent as other modes, it was important to understand how the population, both

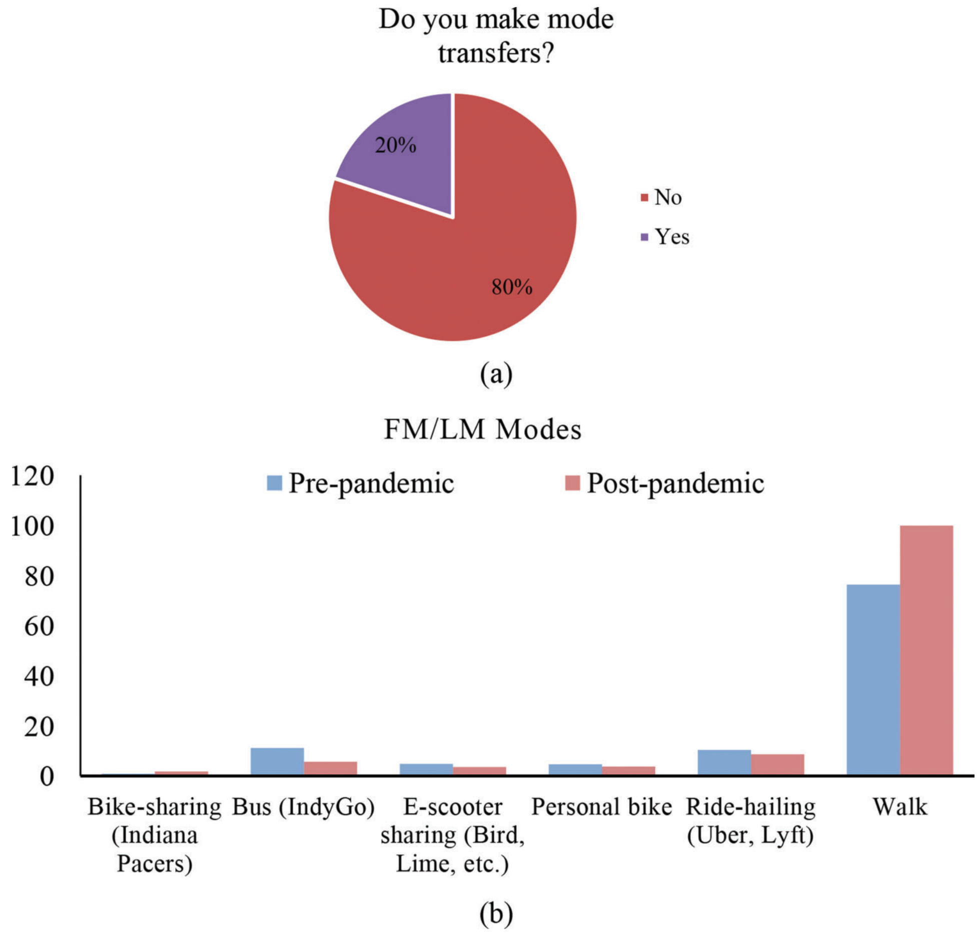


Figure 5.15 (a) Distribution of participants who make mode transfers in a single trip, and (b) modes generally used for FMLM.

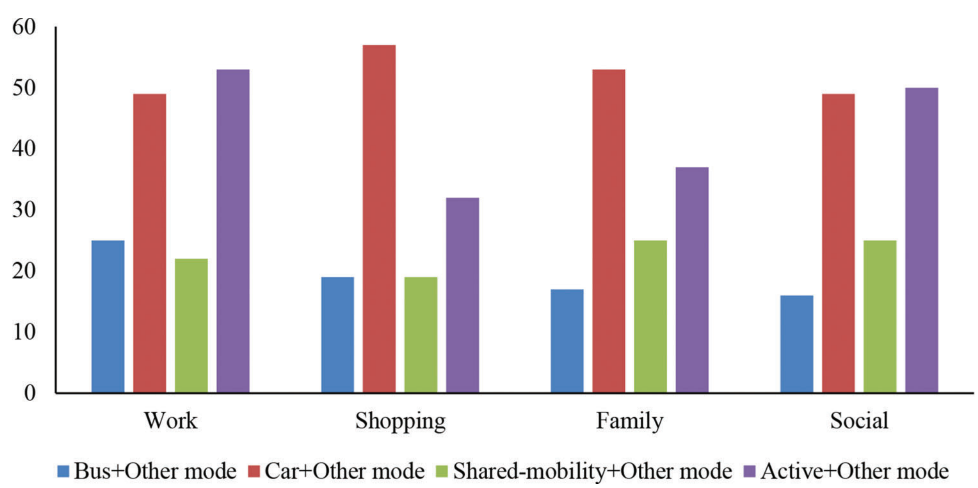


Figure 5.16 Modes used in multimodal trips for different purposes.

users and non-users, perceive such services. Figure 5.19 presents some statements that were asked to the participants about transformative transportation technology.

The participants were asked to state whether they agree with these statements or not. It was shown that the majority agrees on the fact that transformative transportation technology isn't the best option in poor weather. On the other hand, most participants do agree that transformative transportation technology solves the issue of finding a parking spot and grants more freedom to travel around downtown. However, very few agree that transformative transportation technol-

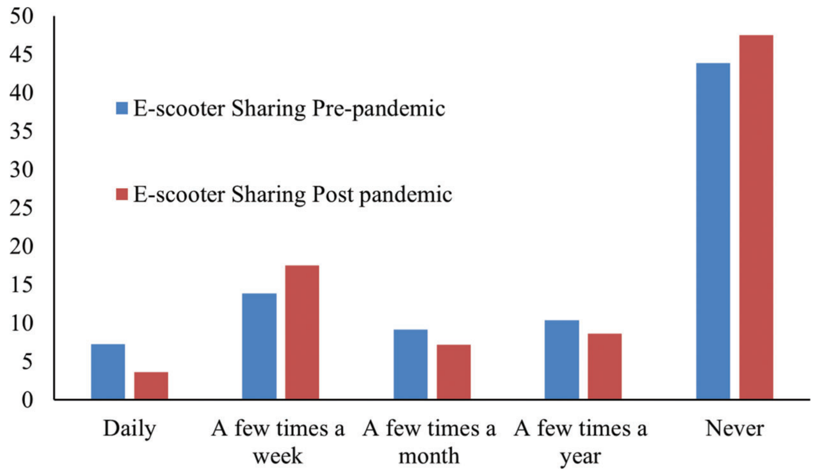


Figure 5.17 E-scooter usage to access the bus.

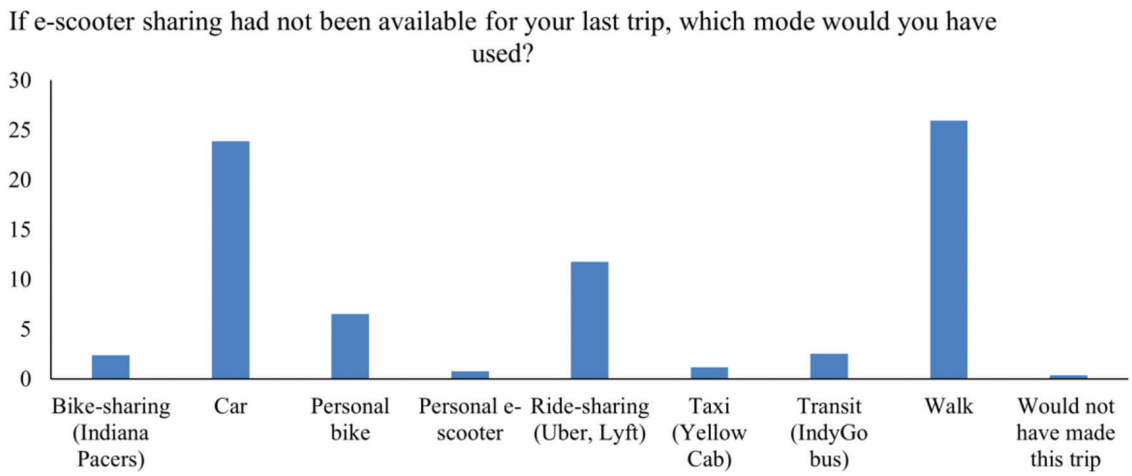


Figure 5.18 Usage of other modes in case e-scooters were not available for the last trip.

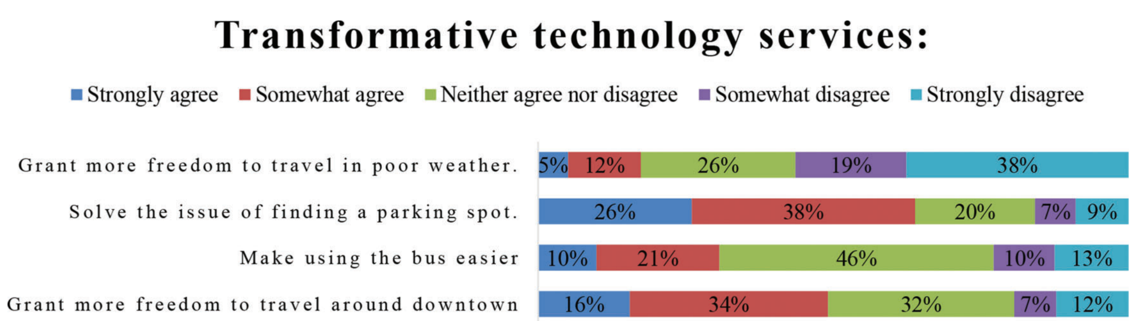


Figure 5.19 Statements about transformative transportation technology.

ogy makes using the bus easier, and the majority is neutral. This shows that the idea of using transformative transportation technology to connect to the bus still isn't a trend in the city and that people use these modes in other contexts.

Next participants were asked to rate each mode for how likely it is to contract COVID-19 from using it (Figure 5.20). The majority think that the probability of contracting COVID-19 is average to high if using ride-hailing, taxi, or bus. Fewer participants think that e-scooters and bike-sharing are as dangerous. This can be linked to the fact that the latter services aren't concurrently used with other users. It is likely that the thought of simultaneously sharing the service with other people is what makes users perceive it as more dangerous.

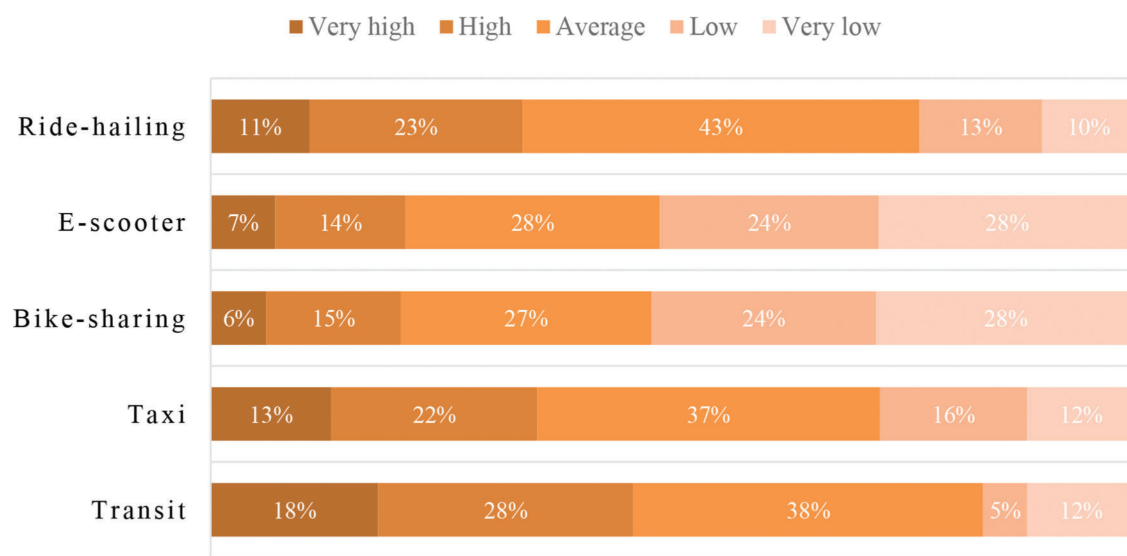


Figure 5.20 Probability of contracting COVID-19 from using different transformative transportation technology modes.

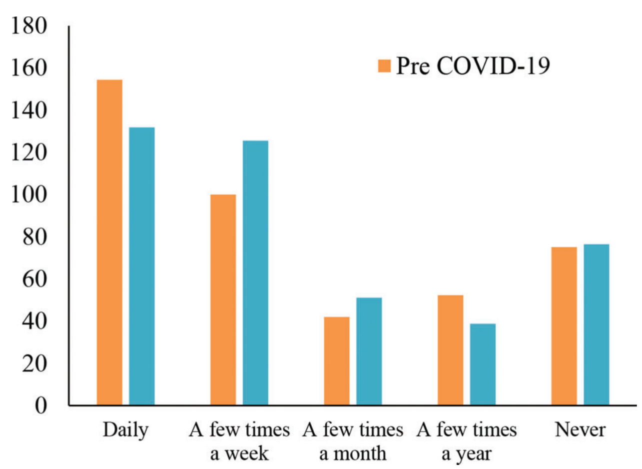


Figure 5.21 Walking frequency pre-COVID-19 and during COVID-19.

5.2.3.1.4 Stated impact of COVID-19 on travel behavior. It is no surprise that COVID-19 has had an effect on the transportation system in general. Hence, it was of interest to dig deeper and explore how transportation was influenced by the pandemic. This section discusses the change in mode choice and trip purpose due to COVID-19, with further analysis of the importance of some attributes in a work trip.

The survey asked participants to report their usage frequency of several modes pre and during the pandemic. The results for some modes are shown in Figure 5.21, Figure 5.22, and Figure 5.23.

Modes were affected differently and that was apparent from the subsequent figures as well as an additional non-parametric test. Figure 5.21 shows that most participants walk frequently, and that the frequency of walking is overall distributed.

While there was a slight drop in daily walking trips, it was shown that more participants who walk a few times a week increased after COVID-19. This can be explained by the fact that the overall number of trips decreased, which is reflected in all modes in general, including walking.

On the other hand, the car was more widely used on a daily basis (Figure 5.22). The number of daily users dropped during COVID-19, potentially because they are making fewer trips. This explains the increase in users who drive a few times a week.

Additionally, people were asked about their transformative transportation technology usage frequency (Figure 5.23). Most users don't use ride-hailing as much as they use cars. They use this mode less frequently. However, what was noticeable is that more people during COVID-19 stated that they are using the service less frequently. More than 50 participants stated that they are never using ride-hailing again during COVID-19. This can be linked to their risk perception of the pandemic and their perception of transformative transportation technology in general.

To further understand the difference in mode usage frequency because of COVID-19, the marginal homogeneity test was performed on the sample. It is a non-parametric significance test. It aims at comparing two dependent samples to study if they match or correlate (White et al., 1982).

The test's parameters are shown Table B.10 in the appendix. A p-value$<$0.001 shows that the hypothesis that ride-hailing usage frequency stayed the same during COVID-19 can be rejected. The test suggested that the usage of all modes significantly changed because of the pandemic. However, for walking, although there was a change, it was not as significant as the others. Please note that this test was repeated for the other modes. The corresponding tables of the parameters can be found in Table B.10 and Table B.11 in the appendix.

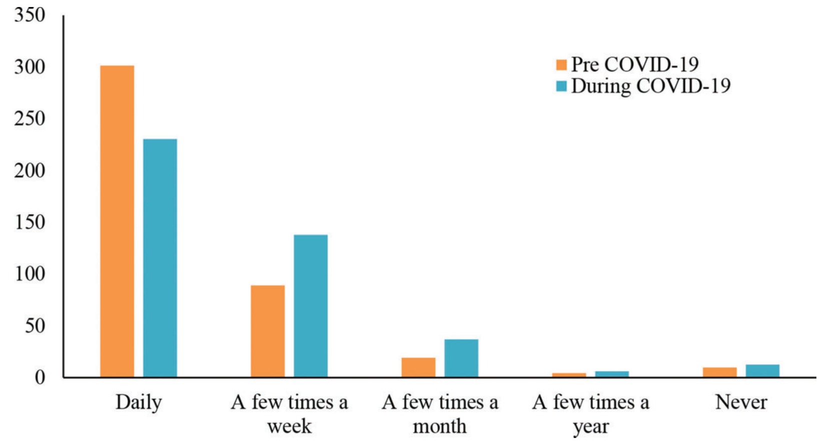


Figure 5.22 Car usage frequency pre-COVID-19 and during COVID-19.

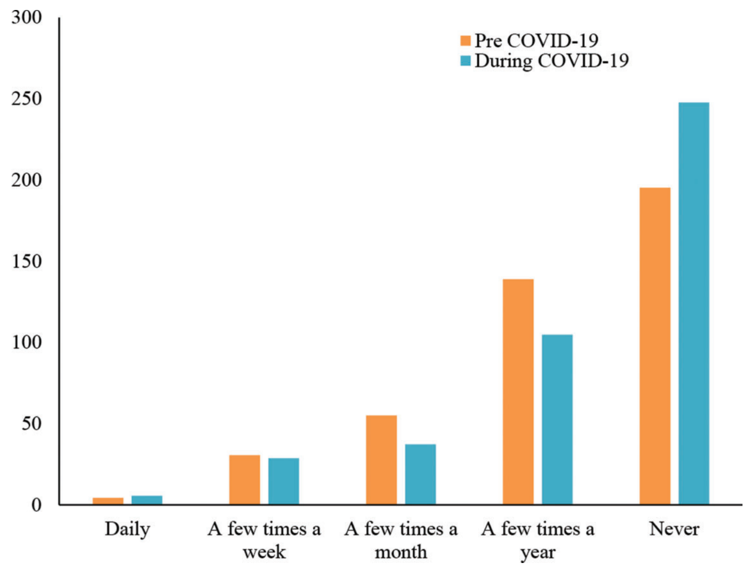


Figure 5.23 Ride-hailing usage frequency pre-COVID-19 and during COVID-19.

One of the other outputs of this statistical test is a cross-classification frequency table (Figure 5.24). The figure shows that there is a significant number of users who used to use ride-hailing a few times a month before the pandemic and now are either using it a few times a year or never. Additionally, more than 50 users who used to depend on ride-hailing a few times a year stated that they would never use ride-hailing after the pandemic.

Participants were asked about their trip frequency for different trip purposes—work, shopping, personal, and social. Overall, the number of trips decreased for all purposes, which was indicated by a drop in frequency.

Figure 5.25a shows that there was a drop in daily work trips after COVID-19, but also a slight increase in trips made a few times a week. This can be linked to many factors. One of them is the emergence of telecommuting trends and not having to commute every day to work. Another factor might be unemployment related to COVID-19. The nation suffered from a wave of unemployment after the pandemic came about.

Another trip purpose that was of interest is shopping. Figure 5.25b shows a drop in daily and weekly trips for shopping purposes. However, an increase in monthly trips can be seen. This shows that a good number of people refrained from going on shopping trips and shifted their habits by going less frequently. One reason behind that is the fear of infection caused by the presence of other people in the supermarkets. Another reason, which can be further looked into in future projects, is online shopping and delivery platforms. These services had started before COVID-19 but gained a huge boost after the pandemic came about given their convenience. Thus, it's not surprising to see people decreasing the frequency of their shopping trips given that more alternatives are present nowadays.

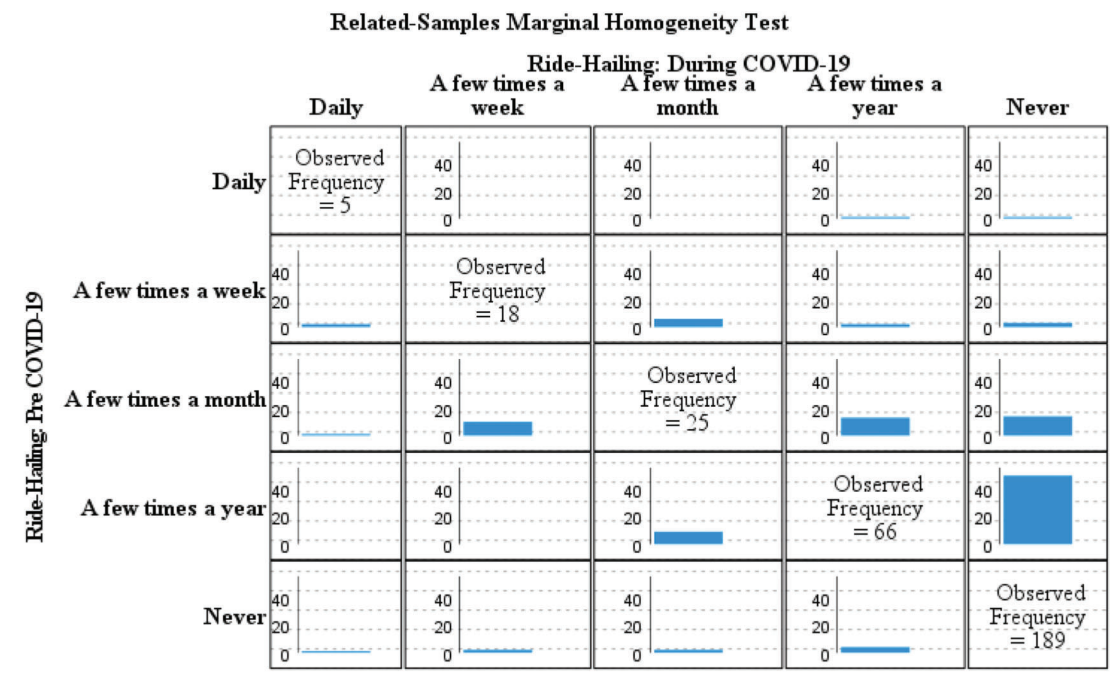


Figure 5.24 Cross classification frequency table for ride-hailing.

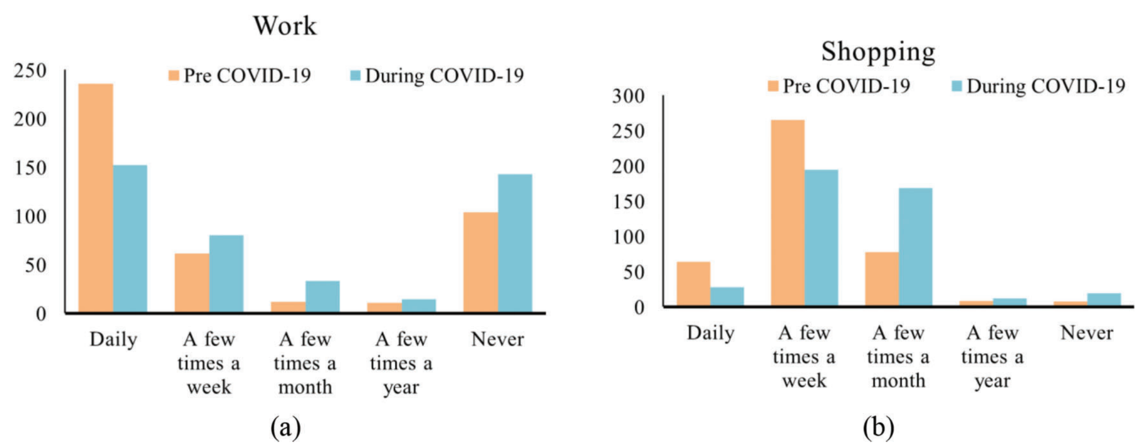


Figure 5.25 Trip purpose frequency for pre-COVID-19 and during COVID-19: (a) work and (b) shopping.

To help understand more the trends regarding the different trip purposes, several marginal homogeneity tests were performed. All tests came back significant except for work (shown in Table B.11). This means that change was significant for shopping, personal, and social trips but not for work trips (Table B.11, p-value = 0.122). However, this does not mean that there was not a change in work trip habits. It only suggests that the difference was not statistically significant. This makes sense since out of the four trip purposes, work appears to be the most important and least flexible. People can forgo social trips for instance, but they are less likely to do the same for work trips.

Additionally, Figure 5.26 details how participants are changing their work trip frequency. A decent number of people still go to work daily (n = 130). However, some daily commuters now go to work a few times a week, and a few go a few times a month. We can notice that some of the previous commuters never go to work now. This can suggest that these participants lost their jobs or now work fully remotely.

5.2.3.2 Analysis of the choice experiment. As we discussed above, we successfully collected 426 respondents, and each respondent made their choice across nine scenarios (one base scenario with eight alternative scenarios) for both recreational (Choice Experiment 1) and commuting (Choice Experiment 2) trip purposes. After cleaning the survey data (e.g., excluding respondents who do not answer all mode choice questions

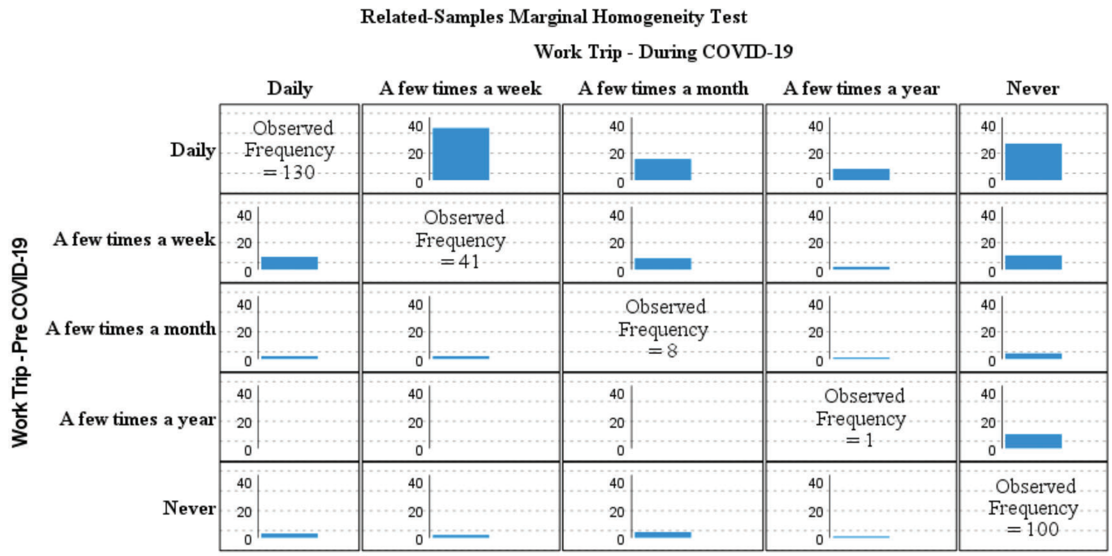


Figure 5.26 Cross classification frequency table for work trips.

or demographic questions), we obtained 394 valid respondents for mode choice analysis.

Table 5.7 and Table 5.9 summarize the descriptive statistics of the main commuting mode and demographic information of survey respondents. About 87% of respondents stated that private vehicles are their main mode of commuting, indicating the potential high vehicle usage. Only 6% of respondents rely on the public transit system for daily commuting. The current bus system in Indianapolis can be improved to meet more people's travel demands. One viable way is to integrate transformative transportation technology with the bus system and the multimodal system could replace more vehicle trips. The demographic distribution, such as age, gender and household income, does not fully represent the local distribution based on the ACS. We have also added a weight to each respondent in the data analysis and mode choice modeling to eliminate the impacts of sampling bias (details in Chapter 5.2.2.3).

Figure 5.27 shows the choice frequency across different modes for recreational and commuting trips in the base scenario, respectively. In the base scenario in which transformative transportation modes are not available, for the short recreational trip (1 mile), 53% of respondents prefer to use private vehicle while 38% would like to walk. For the longer commuting trip (6 miles), more people (85%) selected private vehicles and 11% chose the bus. Although the result is based on two pseudo trips (details in Chapter 5.2.1.4), the mode shift pattern still suggests that people in Indianapolis highly rely on private vehicles for their daily life before having alternative options offered by transformative transportation technologies.

With the awareness of transformative transportation technologies, respondents may change their mode choice when the availability and cost are changing. Figure 5.27 shows the mode choice frequency in different alternative scenarios. For the recreational trip, compared with the base scenario, the result shows that there are about 10% probability that people could shift from private vehicle (53% to 42.4%) to other transportation modes when the availability and cost become more attractive. However, for commuting trips, the mode shift from private vehicle to other modes is rarely happening. Although transformative transportation modes can integrate with the public transit system and encourage multimodal trips, many of these trips are shifted from *bus + walk*, not from private vehicle. Transformative transportation modes are used to reduce efforts of walking for connecting to the bus service, but not to reduce private vehicle usage. Obstacles still exist in promoting multimodal services to replace private vehicles.

5.2.3.2.1 Mode choice modeling. Mode choice models are mathematical expressions that are used to estimate the modal shares of the travel market given the time and cost characteristics of the various competing modes considering the demographic and socio-economic characteristics of the users.

We chose multinomial logit (MNL), one of the most commonly used techniques in the travel behavior analysis field, to build the mode choice model and quantify the impacts of travel cost, travel time, and the demographic patterns to their mode choice under different trip purpose based on the maximum utility theory. The standard mathematical formulation of MNL (Washington et al., 2020) is

$$P_i = \frac{e^{U_i}}{\sum_I e^{U_i}} \qquad \text{(Equation 5.2)}$$

where I is the set of all available alternative travel modes, P_i is the probability of choosing mode i, and U_i is the utility function of mode i.

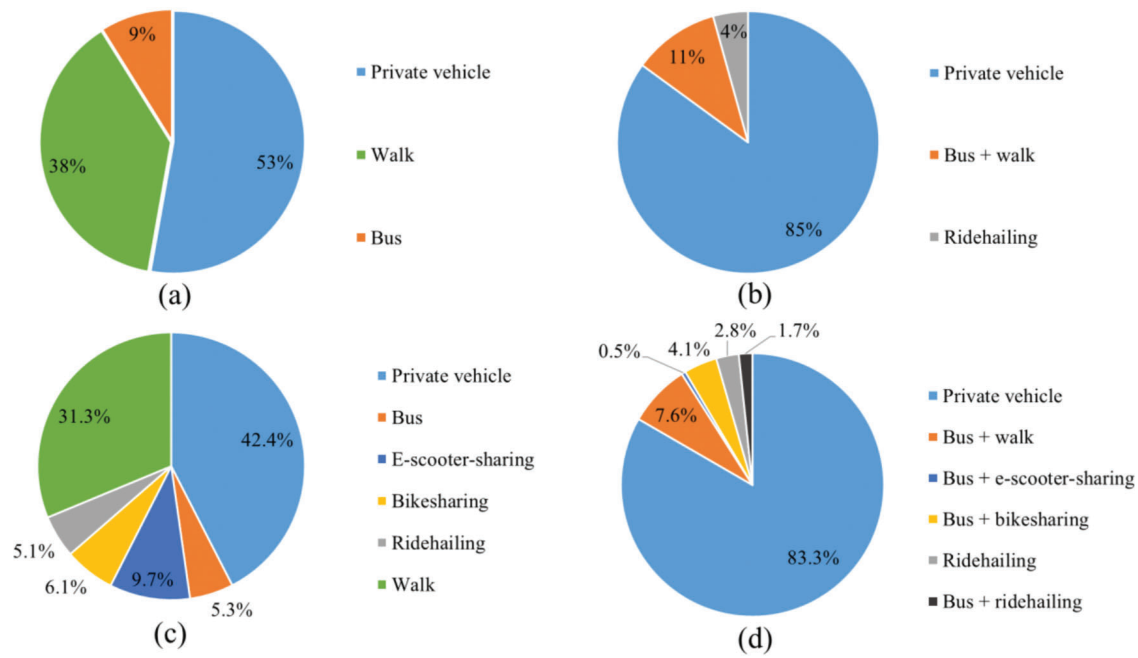


Figure 5.27 Mode choice frequency of different modes by trip purpose. (a) Recreational trip (choice experiment 1) in base scenarios; (b) commuting trip (choice experiment 2) in base scenarios; (c) recreational trip (choice experiment 1) in alternative scenarios; and (d) commuting trip (choice experiment 2) in alternative scenarios.

The utility function for each mode i can be formulated as

$$U_i = \beta_{i0} + \beta_1 \times COST + \beta_2 \times INVEH + \beta_3 \times OUTVEH + \beta_{i4} \times SE + \varepsilon_0 \qquad \text{(Equation 5.3)}$$

where β_{i0} is a constant specific for mode i to capture the overall impacts of each mode that cannot be explained, such as comfort, safety, convenience, etc. COST, INVEH, and OUTVEH are independent variables of travel cost, in-vehicle travel time, and out-of-vehicle travel time, respectively, that we set for different scenarios. β_1, β_2, and β_3 are the estimated parameters, respectively, to quantify the impacts. SE represents a group of socio-demographic variables of respondents, such as age, gender, household income, household size, number of children, education level, race, etc. After model selection, we included gender, household size, and age as the socio-demographic variables in our mode choice model, and β_4 is a vector of estimated parameters for these selected socio-demographic variables. ε_0 is the error term to capture the variance of individual choice, which is assumed to be independently and identically distributed.

This study will use the MNL model to estimate two groups of utility functions for recreational and commuting trips based on the stated preference choice experiment data that were collected from the survey. We used the maximum likelihood estimator to solve the parameters ($\boldsymbol{\beta}$) that best fit the respondents' choices.

The MNL estimation results for recreational trips and commuting trips are listed in Table 5.10 and Table 5.11. All estimated socio-demographic parameters included in the model are statistically significant and the signs are plausible. We set the mode of *walk* and the mode of *ride-hailing* at the reference level for recreational and commuting trips, respectively, whose estimated parameters are fixed to be zeros.

5.2.3.2.2 Discussion and implications. For a short (1 mile) recreational trip, private vehicle is estimated to have the highest constant value, which means that the private vehicle has better convenience, safety, or comfort that makes it the preferred mode to choose, compared with other travel modes. E-scooter has the lowest constant, showing the least willingness to use it because of the higher cost compared with other modes (Chapter 5.2.1.4). In general, although all three variables are significant, travel cost is a more important factor that affects people's mode choice, compared with in-vehicle and out-of-vehicle travel time.

For a long (6 mile) commuting trip, people have a dominant preference of choosing private vehicles based on the estimated constant. *Bus + bike-sharing* multimodal mode is the least preferred because of the active efforts required to ride a bike for a long trip distance, even if bike-sharing is a much cheaper mode than ride-hailing or "shared e-scooter" to serve the first/last mile connection. Travel cost is still an important factor. In-vehicle travel time is not statistically significant, which is because the in-vehicle travel time is similar under different scenarios and the change of price or availability may not have a significant impact on the in-vehicle time.

The estimated mode choice model shed light on how people in Indianapolis make choices across different

TABLE 5.10
Multinomial logit model estimation results—recreational trips

Mode	Estimated Parameters					
	Private Vehicle	**Bus**	**Shared E-Scooter**	**Bike-Sharing**	**Ride-Hailing**	**Walk (reference)**
Constant	0.832**	-1.456***	-1.929***	-1.733***	-1.296**	
Cost				-0.165***		
In-Vehicle Time				-0.042***		
Out-of-Vehicle Time				-0.079**		
Respondent is male? (1: Yes; 0: No)	0.362***					
Respondent's household size?	0.352***		0.394***	0.293***	0.393***	
Respondent is younger than 35? (1: Yes; 0: No)	0.493***	-0.682***	0.395***	0.380**	0.458***	

Note:
**Represents the statistical level at 5%.
***Represents the statistical level at 1%.

TABLE 5.11
Multinomial logit model estimation results—commuting trips

Mode	Estimated Parameters					
	Private Vehicle	**Bus + Walk**	**Bus + Shared E-Scooter**	**Bus + Bike-Sharing**	**Ride-Hailing (Reference)**	**Bus + Ride-Hailing**
Constant	1.954***	-0.763***	-3.965***	-4.414***		-2.272***
Cost				-0.420***		
In-Vehicle Time				-0.005		
Out-of-Vehicle Time				-0.131**		
Respondent is male? (1: Yes; 0: No)	-0.869***			-0.545**		-1.111***
Respondent's household size?		-0.444***	0.325***	0.320***		
Respondent is younger than 35? (1: Yes; 0: No)	1.045***		0.815***	0.715***		1.248***

Note:
**Represents the statistical significance at 5%.
***Represents the statistical significance at 1%.

conventional and transformative transportation modes, considering the impacts of travel cost, in-vehicle time, out-of-vehicle time, as well as the preference of different groups of people. Although private vehicles have the highest overall preference, due to better safety, convenience, and comfort, leading to being the dominant mode, transformative transportation modes, such as shared e-scooter, bike-sharing, and ride-hailing, still can potentially replace car trips and reduce vehicle usage. Based on our analysis, improving the availability (decreasing out-of-vehicle time) and reducing the cost of transformative transportation modes could encourage people's mode shift from private vehicle to transformative modes or integrated multimodal trips with the public transit system.

With the rapid development of transformative transportation systems, it is very likely that availability and cost could change in the future, leading the different mode choice patterns. In Chapter 7, we will present an agent-based simulation model, which integrates the conventional and transformative transportation modes in one system, to understand how the mode choice would affect the local travel demand, especially private vehicle usage. We applied the estimated mode choice model as the travel behavior basis for the simulation to analyze the impact under different transformative system adoption scenarios.

5.3 Chapter Summary

The analysis of spatiotemporal data helped identify different usage patterns of transformative transportation services across different cities (Chapter 3). While the results provided insight for how the services were being used, the analysis could not shed light on who uses these services. Information about users' characteristics (preferences, behaviors, demographics, etc.) is equally as important.

To achieve this, two surveys were conducted in two Hoosier cities. The first survey was conducted in

Greater Lafayette. Its main aim was to compare the two shared micro-mobility services operating in the city. Results showed that most respondents use shared e-scooters out of curiosity while they use bike-sharing to save time because it is quicker than walking. Additionally, a similar trend was identified for both services in the context of COVID-19. Usage frequency of both services increased during the pandemic; both services were increasingly used to replace non-walking modes.

The second survey was distributed in Indianapolis. It explored the impact of transformative transportation services on travel demand and travel behavior. Descriptive analysis suggested a significant change in travel habits caused by COVID-19. Similar to the survey in Greater Lafayette, results showed that both transformative transportation modes exhibited similar trends during COVID-19. The analysis provided further insight into the demographics of transformative transportation technology users in the city, as well as their preferences regarding the services. The survey also included a mode choice experiment which was used to develop a multinomial logit model to estimate the factors affecting people's mode choice behavior. Results showed that private vehicles are preferred for both short recreational and longer commuting trips when compared with other traditional and transformative transportation modes. Generally, travel cost was found to be more important than in-vehicle and out-of-vehicle time.

6. IMPACTS OF TRANSFORMATIVE TRANSPORTATION TECHNOLOGIES ON THE PUBLIC TRANSIT SYSTEM

Evidence from existing literature (Chapter 1) and survey results (Chapter 5) indicates that transformative transportation technologies could either compete with the public transit system to replace transit trips or complement transit to extend the transit service. But the existing literature to evaluate the relationship between shared e-scooters and bus systems is largely survey-based. While the survey results have provided important and useful insights, they have the limitations of being generally qualitative and lacking spatial and temporal details. Understanding how transformative transportation technologies compete with or complement the transit system in different areas and during different time periods is critical to inform strategic shared e-scooter system development alongside public transit operations. Part of this chapter has been published in the journal *Transportation Research Part D: Transport and Environment* (Luo et al., 2021).

6.1 Introduction

This study proposed a modeling framework to estimate the impact of transformative transportation technologies on local public transit systems. Using transformative transportation trip data and transit data, the model can investigate the complementary and competing relationship between each trip and public transit, with spatial-temporal details. In this chapter, we will use the shared e-scooter system and the bus system in Indianapolis as a case study to introduce the model structure and outputs. The modeling framework can be easily transferred to other transformative transportation systems in other Indiana cities if similar data is available.

6.2 Shared E-Scooter and Transit Data in Indianapolis

For the shared e-scooter data, we used the trip-level data that was introduced in Chapter 3.1, which includes the trip origin and destination information. For the bus system, we used the General Transit Feed Specification (GTFS) data to collect the schedule and network information of the IndyGo bus system in Indianapolis (Google, 2020). The GTFS data contains the geographic locations (longitudes and latitudes) of the bus stops, shapes of each route, schedule timetable, and the trip information of each bus route. Each stop includes a unique stop ID, the name of the stop, and the location. Each bus trip (traveling once from one terminal stop to another along a route) has a unique trip ID, route and direction, the sequence of the stops that it will visit, and the corresponding arrival/departure time at each stop. The GTFS dataset for Indianapolis includes 3,425 bus stops and 7,085 bus trips, considering the different schedules for weekdays, Saturday, and Sunday. In addition, we obtained transit ridership data from IndyGo to investigate the impact of shared e-scooter usage on bus ridership. The data is from January 2017 to December 2019, covering the periods before and after the launch of the shared e-scooters. The ridership dataset includes the number of boarding and alighting at each stop for each bus trip, as well as the stop ID (consistent with stop ID in GTFS) and bus arrival time at each stop.

6.3 Relationship Classification Model

Each shared e-scooter trip could potentially compete with, complement, or have no impact on the bus system, depending on the trip time, location, and the existing bus infrastructure and bus schedule. A shared e-scooter trip is considered as a potential *competing trip* if the existing bus system can serve this demand within the reasonable trip duration, walking distance, waiting time, and transfer time. In other words, it is feasible for such a trip to be served by bus if the e-scooter system did not exist, indicating the possibility of the e-scooter trip substituting the bus use. Please note that here we are only focusing on the feasibility of the competing relationship, which can be viewed as the upper bound of the competing impact. It is possible for people to use other transportation modes for trips that could be conveniently served by bus.

No impact trips represent trips for which users would not take the bus when the e-scooter system was not available, even if bus service was available. These are short trips that, although taking the bus is possible, the relative distances between walking to/from the bus stops and walking directly from the trip origin to the destination makes taking the bus unfavorable (Figure 6.1a). In this case, we consider the e-scooter trip as potentially replacing walking. Since e-scooter trips are mostly short, we only considered walking as the alternative mode (besides taking the bus) in this study.

The shared e-scooters can also potentially complement the existing bus system, serving as the mobility extension when the bus service is not available, either spatially or temporally. In this study, we defined the "complementary relationship" with seven impact categories (Table 6.1). (1) The shared e-scooters were used to avoid long detours due to fixed bus routes. For example, the users can ride e-scooters in a straight line to the destination, but the bus route may circle around the blocks, leading to longer travel distances ("Bus distance too long"). (2) The shared e-scooters were used to avoid unacceptable bus waiting time due to the limited bus frequency ("Waiting time unacceptable"). (3) The e-scooter system may serve trips that fall outside of the bus service time such as midnight ("Outside of service time"). (4) The shared e-scooters can satisfy trips that have bus stops near both their origins and destinations, but no appropriate bus route is available to serve the trip (e.g., requiring too many transfers to complete the trips) ("Bus route unavailable"). (5) and (6) The customers may use the shared e-scooters for the first-/last-mile connection to the bus stops ("First-mile connection" and "Last-mile connection"), as shown in Figure 6.1b, c. Trips in these two categories are feasible to use shared e-scooters and bus as an integrated system and could potentially increase bus ridership. (7) The e-scooter system may serve trips outside of the bus service area ("Outside of service area"). For example, in Figure 6.1d, neither the trip's origin nor the destination is close enough to a bus stop, and the e-scooters fill the mobility gap to serve trips that cannot be served by the bus system. Like the competing trips, the complementary relationships defined here only focus on the feasibility of the e-scooter trips to complement the bus system. The complementary relationship does not necessarily bring additional bus ridership.

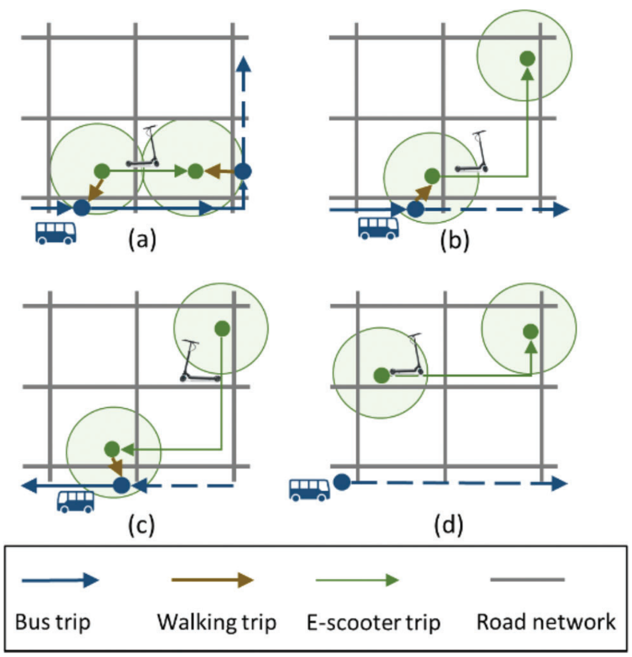


Figure 6.1 Examples of selected impact categories. (a) Replace walking, (b) last-mile connection, (c) first-mile connection, and (d) outside of service areas. The circles indicate the acceptable walking distance.

Figure 6.2 shows an overview of the modeling framework that classifies the potential relationship between each e-scooter trip and the bus system. The input data of this model includes the historical e-scooter trip records and the bus schedule data. For each e-scooter trip, we first identified whether bus stops exist within a pre-determined range r of the trip O and D. We assumed that the coverage buffer of bus stops is a quarter mile (400-meters), which is a commonly used threshold to measure transit coverage (Kong et al., 2020). We also did a sensitivity analysis of the spatial

TABLE 6.1
E-scooter trip classification and impact categories based on its relationship to the existing bus system

						Acceptable		
Relationship	**Impact Category**	**Stop Near Trip O**	**Stop Near Trip D**	**Route Exists**	**Within Service Time**	**Waiting Time**	**Bus Distance**	**Walking Distance**
Competing	Competing with bus	Y	Y	Y	Y	Y	Y	Y
No Impact	Replace walking	Y	Y	Y	Y	Y	Y	N
Complementary	Bus distance too long	Y	Y	Y	Y	Y	N	–
	Waiting time unacceptable	Y	Y	Y	Y	N	–	–
	Outside of service time	Y	Y	Y	N	–	–	–
	Bus route unavailable	Y	Y	N	–	–	–	–
	Last-mile connection	Y	N	–	–	–	–	–
	First-mile connection	N	Y	–	–	–	–	–
	Outside of service area	N	N	–	–	–	–	–

Note: Y = yes, N = no, and – means not applicable.

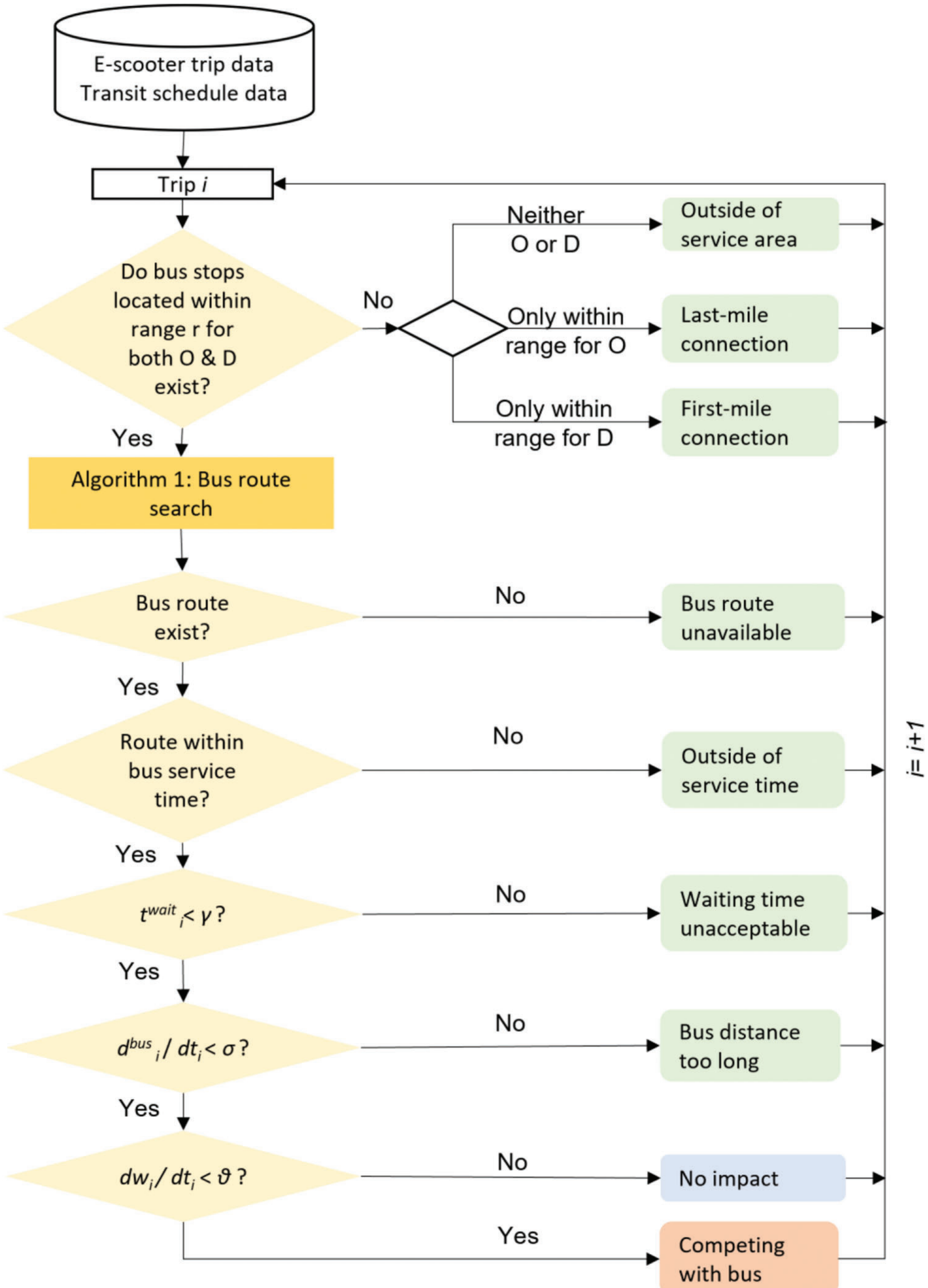


Figure 6.2 Overview of the relationship classification model.

coverage; details about the method can be found in the last paragraph of this section. If no bus stops are within this range for neither trip O nor D, we identified this trip's impact category as outside of service area. If bus stops exist within the range r of either a trip's O or D but not both, the trip was categorized as a *first-/last-mile connection*. For trips whose ODs were both located near bus stops (indicating the possibility of taking the bus to serve the trips), we developed and applied a bus route search algorithm to evaluate the feasibility of serving the e-scooter trip using the existing bus system and search the best bus route. The detailed algorithm can be found in our published paper (Luo et al., 2021).

If no feasible bus route is found for the trip, this trip will be identified as serving a demand for which the bus service is unavailable. If feasible bus routes exist, additional criteria will be applied to further classify the potential impact (Figure 6.2), including (1) whether this trip is outside of the service time (trip start time is later than the arrival time of the final bus trip at the boarding stop, or trip start time is earlier than the arrival time of the first bus trip at the boarding stop; (2) whether the bus waiting time is too long ($\gamma = 10$ minutes, preset maximum acceptable bus waiting time) (Fan et al., 2016); (3) whether the bus route requires too much detour relative to the trip distance ($\sigma = 2$, preset threshold for the acceptable ratio of in-bus distance to total trip distance); and (4) whether the total walking distance to and from the bus stops is too long relative to the trip distance ($\theta = 50\%$, preset threshold for the acceptable ratio of walking distance to trip distance). If the trip could be served by bus with acceptable waiting time, walking distance, and in-bus distance, the e-scooters may have potentially replaced bus to serve the trip.

6.4 Spatial-Temporal Analysis of the Relationship

For each historical e-scooter trip, we applied the proposed relationship classification model to evaluate whether it is feasible for this trip to substitute a bus trip or to provide complementary coverage. We also analyzed the temporal, trip distance, and spatial distributions of the trips with different impact categories to understand during which periods, for what types of trips, and in which areas the e-scooters are competing with or complementing the bus system. Such knowledge can provide insights to inform e-scooter system management and urban planners to develop better-integrated transportation systems.

Overall, 44% of the e-scooter trips likely replaced walking, while about 27% of the trips could potentially compete with bus trips, and 29% complement the existing bus system. Most of the complementary trips played roles of providing service outside of bus service time, shortening bus route distance, and reducing unacceptable waiting time, accounting for 2%, 5%, and 20% of the total trips, respectively. Very few trips (<1%) were identified as potentially serving the first-/last-mile trips to connect to/from the bus system. This result is very different from those reported in big cities (e.g., Chicago), where about 34% of the survey participants reported using e-scooters for transit connections (Chicago Department of Transportation, 2020). This difference may be attributed to big cities having more developed transit systems, the shared e-scooters serving different areas (e.g., the shared e-scooter pilot in Chicago was launched outside of the downtown area) or using different methods (survey versus trip-level analysis) in the studies. In addition, the roles shared e-scooters played are also different from those of bike-sharing systems, especially for serving first-/last-mile trips. Trip-level analysis of station-based bike-sharing systems in four U.S. cities (Boston, Chicago, Washington D.C., and New York City) shows that 25%–35% bike-sharing trips could be used to integrate with public transit to serve the first-/last-mile trips (Kong et al., 2020). One possible reason is that the bike-sharing system provides membership subscriptions (e.g., monthly pass or annual pass) which enables affordable recurring use of the system. Kong et al. (2020) pointed out that bike-sharing subscribers are more likely to use bike-sharing service to connect with public transit, especially for commuting on weekdays. However, the current pricing model of shared e-scooter does not allow such membership plans to encourage users to commute multimodally with shared e-scooter and bus, hindering its potential to serve the first-/last mile trips and complement public transit system.

During the late-night and early morning (after 9 pm and before 7 am), when the bus service is limited, the e-scooters are providing complementary services, as expected (Figure 6.3a). During the periods that the bus service is in normal operation (7 am to 9 pm), the relative shares of different impact categories are quite stable, with replacing *walking* (41%) being the dominant impact category followed by *competing with the bus* (25%). However, because trips that are potentially replacing walking (trips in the *no impact* category) are mainly short trips that are less than one mile (Figure 6.3c), from the perspective of total trip distance, only 15% of the e-scooter miles are from these trips, while over 57% of the e-scooter miles are from trips that could potentially substitute bus system use (Figure 6.3b). The impact categories of complementary trips, including bus trip distance is too long, out of service time, and waiting time unacceptable, contribute to 7%, 2%, and 19% of the shared e-scooter miles, respectively.

Overall, the shared e-scooters in Indianapolis are likely to have more competing impacts than complementary impacts to the existing bus system. Although the number of potentially competing trips are only slightly more than the potentially complementary trips (44% versus 27%), their differences in terms of e-scooter miles are more significant (57% versus 15%).

To evaluate the spatial variations of the roles that shared e-scooters played, we compared the numbers of competing and complementary trips in each grid during different time periods (Figure 6.4a). The grids dominated by complementary trips are in red (the value of 1 indicating all complementary trips), while those dominated by competing trips are in blue (the value of -1 indicating all competing trips). Consistent with what we observed in Figure 6.3a, the shared e-scooter system complements the bus system in most areas in the early morning and late evening, when the bus service is limited. However, during the day, downtown and on the north side of the city, which are serviced by a denser network of bus routes, the shared e-scooter system is more likely to compete with the bus system. In these areas, the travel demands served by the e-scooters can be satisfied by the existing bus system. On the other hand, on the south side of the city, except for areas on the route of Bus 14 (the diagonal route from downtown to the southeast side of the city, Figure 6.4a), the shared e-scooter system tends to complement the bus system and fill in mobility gaps. A similar trend has also been found for the bike-sharing system in Washington D.C., showing that the bike-sharing system has a higher

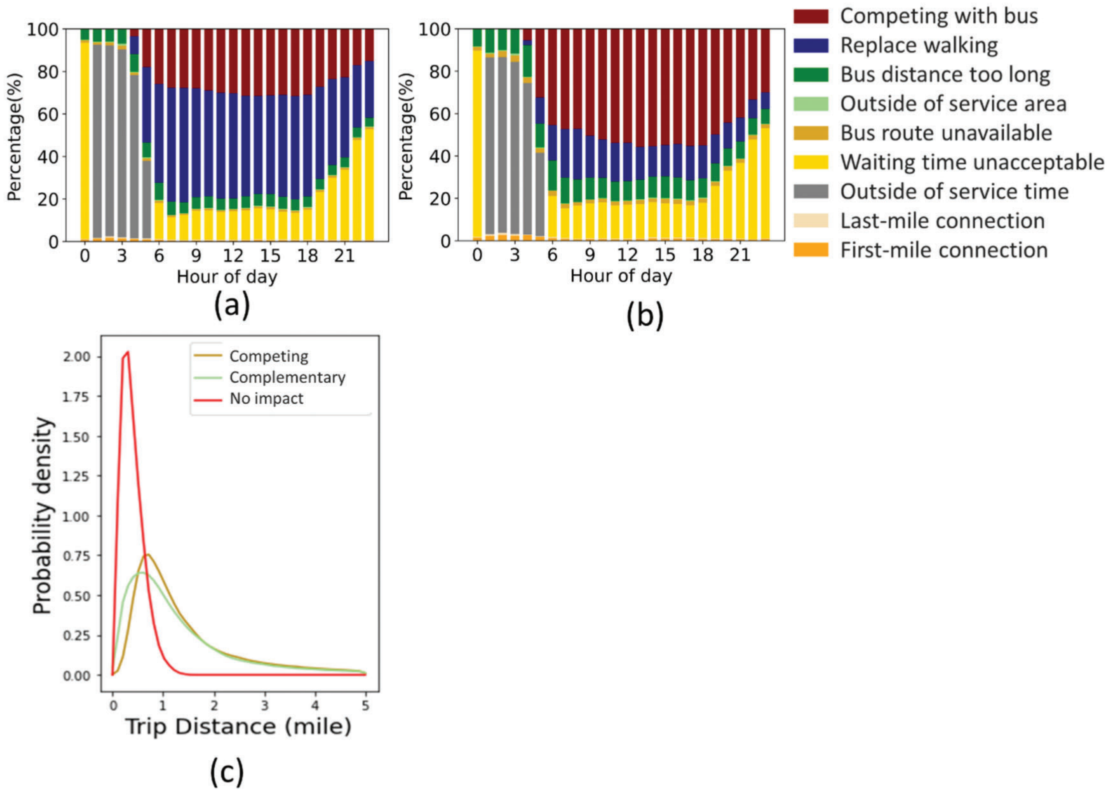


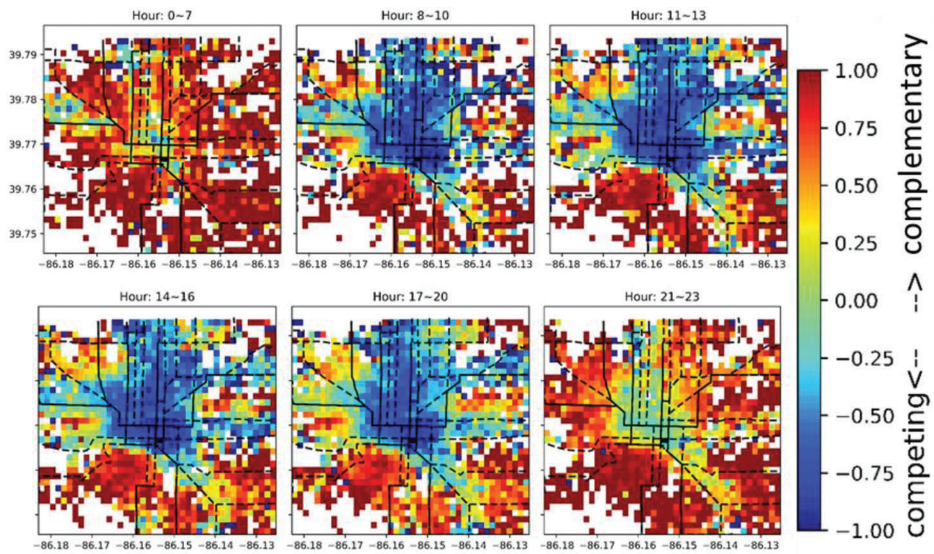
Figure 6.3 (a) Impact composition of trip distance at different times of the day, (b) impact composition of trip distance at different times of the day, and (c) trip distance distribution by impact categories.

potential to complement the public transit system in the urban periphery than in the urban core (Martin & Shaheen, 2014). Additionally, most of the trips (over 90%) that are potentially substituting walking are concentrated in downtown. These results show that, if Indianapolis would like to better develop the shared e-scooter system to complement the existing bus service, it is important to encourage the operators to place more e-scooters outside of downtown, especially on the south side of the city. Although more trips are currently taken downtown, most of these trips are likely to either substitute walking or bus use, providing limited benefit to the city's transportation sustainability (McGuinness, 2019).

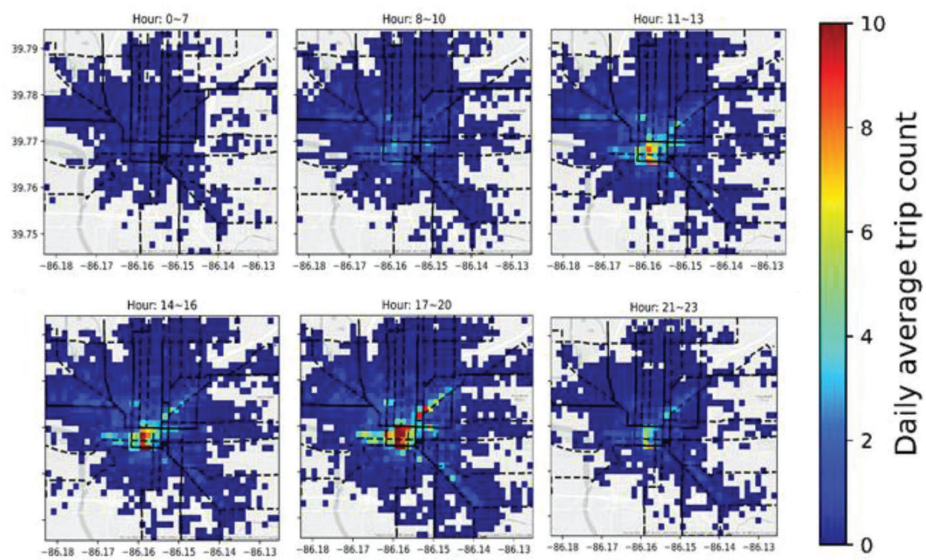
The e-scooter reposition strategy may substantially determine where the e-scooters are available for use and can be designed to promote the complementary relationship between the two systems. The current repositioning strategy moves most vehicles to downtown. While such a repositioning strategy redistributes the e-scooters to areas with higher trip densities, it may not help fill mobility gaps in the city. Redistributing more e-scooters to the peripheries of the downtown areas where the bus service is limited can enable more complementary trips. In addition, the system usage rate and efficiency may also be improved with the potential increase in utilization rates.

To evaluate whether the potentially competing trips identified using the classification model have actually led to transit ridership change, we built a difference-in-differences (DID) model to validate our classification results. DID models are commonly used to estimate the effect of a specific variable (e.g., policy change) by comparing the differences in outcomes between the treated and control groups (Ma et al., 2019). It can estimate the impact of the variable to the treatment group considering the general trend of the control group and remove the biases in the post-intervention period. Thus, we used the DID method to investigate the difference in bus ridership before-and-after the launch of shared e-scooters and account for the bias when comparing different transit stops in different time periods (detailed method can be found in our published paper (Luo et al., 2021)).

Results from the e-scooter study area show that the competing shared e-scooter trips could lead to a significant ridership reduction. Relative to the control group (stops that are not facing competing impact), every ten-competing e-scooter trips could cause an additional 7.3% daily ridership reduction in the treatment group (stops that are facing competing impact). The number of competing e-scooter trips ranges from 10 to 50 per day at each stop in the treatment group, which leads to 7.3%–36.5% additional daily ridership reduction compared to the stops in the control group. In addition to the daily stop-level impact, we also analyzed the total ridership change for the entire county to understand the magnitude of e-scooter's impact at the



(a)



(b)

Figure 6.4 Spatial distributions of the different roles shared e-scooters played during different time periods. (a) The net complementary/competing effects the shared e-scooters had in each grid (150 m × 150 m). The value of 1 (in red) and -1 (in blue) indicate all trips in that grid are complementary or competing trips, respectively, while the value of 0 (in green) shows an equal number of the two. (b) The heatmaps of the average number of no impact trips (potentially substituting walking) in a day started from each grid (150 m × 150 m).

system-level. Over the course of study period, the total ridership in the control group was reduced by 8.6%, which means that, in general, the bus ridership has an 8.6% decreasing trend. However, considering the total ridership decrease (13.9%) in the treatment stops, the total ridership of the entire county decreased by about 9.6% after e-scooters started operation. In short, these results can be inferred that the bus ridership was further decreased (by about 1%) because of e-scooter's operations in the city.

In summary, the results from the DID models show that shared e-scooter trips being identified as potentially competing with bus resulted in bus ridership reduction. This result also in a way validates the proposed trip classification model—the potentially competing trips did have competing effects.

6.5 Chapter Summary

This study proposed a modeling framework to investigate the relationship between shared e-scooter systems and existing bus systems, considering the spatiotemporal feasibility of serving the trips by bus. Applying the model to the shared e-scooter system in Indianapolis, Indiana as a case study, we evaluated whether shared e-scooters competed or complemented the existing bus system during different time periods, in different areas, and for different types of trips. Results from this study can provide several insights to shared e-scooter companies and urban planners to improve urban mobility and transportation sustainability synergistically. First, most of the shared e-scooter trips in Indianapolis were likely to substitute walking trips or compete with the existing bus service. The shared e-scooter system mainly complements the bus system during the time when bus operation is limited or on the south side of the city where the bus coverage is low. Second, trips that provided complementary service were mainly located outside of downtown, in the areas where the bus service is limited. Very few e-scooter trips were identified to serve the first-/last-mile trips to connect to/from bus stops. Third, the current repositioning strategy, which redistributes most e-scooters to downtown, encourages trips to replace walking or compete with the bus service. In summary, although the shared e-scooter system has the potential to complement the bus system and improve urban mobility and transportation sustainability, the system operation and regulation need to be carefully designed to achieve the benefit.

The above-mentioned results also have the following policy implications for shared e-scooter system evaluation, design, and operation. First, we suggest city planners consider the impacts on existing transportation as part of the evaluation metrics for shared e-scooter system design and operation. A data-driven approach (e.g., the framework we proposed) can help quantify the new system's mobility impacts and provide insights for system improvement with spatial-temporal details. Second, an integration between shared e-scooters and public transit is the key to improving transportation sustainability. Although the current distributions of shared e-scooters could improve downtown mobility, the competing relationship may cause transit trip replacement. Mode shift from public transit to shared e-scooter could increase GHG emissions (average emission factor of a shared e-scooter trip is 202 g CO_2-eq/passenger-mile compared to 82 g CO_2-eq/passenger-mile for a bus trip) (Hollingsworth et al., 2019). The current shared e-scooter system in Indianapolis highly overlaps with the bus system downtown, resulting in many competing trips and being unable to benefit urban sustainability. For shared e-scooter system to provide the emission reduction and sustainability benefits, the key is to integrate it with the transit system and replace automobile usage (e.g., private vehicle or ride-hailing). Third, more efforts are needed to encourage complementary effects and reduce the barriers of system integration. City planners may re-evaluate the fleet size cap for shared e-scooters in areas outside of downtown, where riders may use e-scooters for complementary purposes, but currently have limited shared e-scooters availability. A requirement on distributing more e-scooters to locations that the transit system cannot fully cover may help promote the complementary relationship. For day-to-day operations, we also suggest e-scooter operators reposition a proportion of the e-scooters to areas that are outside of downtown. Although repositioning may cause additional vehicle-miles-traveled, such operation could lead to net environmental benefits if the repositioning can facilitate multimodal trips and reduce private vehicle usage. In addition, the relatively high cost of shared e-scooter usage may discourage frequent use (e.g., by commuters) and hinder modal integration. Evidence from bike-sharing system shows that frequent users are more likely to use it as first-/last-mile connections for commuting (Kong et al., 2020). Shared e-scooter operators are encouraged to offer membership (e.g., monthly or seasonal pass) subscription with a lower cost per use, which could attract more frequent users to commute using shared e-scooters to connect to the transit system. Meanwhile, a close collaboration between the public and private sectors is essential for modal integration. For example, adding e-scooters into transit trip planning platforms can provide availability information for the first-/last-mile connection and reduce the information barriers for the multimodal trips. However, this improvement requires data sharing among different sectors, including public transit, e-scooter companies, and trip planning platforms. Enabling the reservation and payment for the entire multimodal trip can further remove payment barriers and encourage modal integration but requires closer collaborations among different stakeholders. A synergetic system planning, design, operation, and evaluation is critical for improving the complementary effects between shared e-scooters and existing public transit systems and enhancing urban transportation sustainability.

While the results and policy implications discussed above are from the case study of shared e-scooter system in Indianapolis, the proposed framework that investigate e-scooter's impact on bus can be easily transferred to other cities if shared e-scooter trip data and bus schedule data are available. The proposed framework can generate relationship results with spatial and temporal details for city planners to evaluate and regulate the shared e-scooter system. Knowing when, where, and the extent of what impacts on other modes will allow the planners to strategically develop an integrated and sustainable shared e-scooter system for their city's inhabitants to use. The same framework can also be applied to evaluate the relationship between different shared mobility systems (e.g., bike-sharing and ride -hailing service) and other public transit systems (e.g., subways). As more cities are launching shared mobility programs to improve urban transportation systems, the framework offers a tool for urban planners to investigate the impacts on the city's existing transportation system.

7. ASSESSING THE IMPACTS OF TRANSFORMATIVE TRANSPORTATION TECHNOLOGIES ON VEHICLE USE

7.1 Introduction

Chapter 6 analyzed the impacts of transformative transportation technologies on the public transit system and used shared e-scooter system as a case study. In addition to transit, transformative transportation technologies could also significantly change vehicle usage and ownership. Accessing the impact of transformative transportation technologies on vehicle usage is essential for local transportation system development because traffic congestion, fossil fuel consumption, and GHG emissions are all related to vehicle usage (Tirachini, 2020). Vehicle ownership and VMT are two metrics to estimate the impacts on vehicle usage.

There are several ways that transformative transportation technologies can increase or decrease VMT, by competing or integrating with other transportation modes such as private vehicle, taxi, public transit, or other types of transformative transportation systems. First, transformative transportation technologies could be used to directly substitute other traditional transportation modes. If replacing vehicle trips, such as private car or taxi trips, transformative transportation technologies could reduce the VMT and benefit urban mobility (Chicago Department of Transportation, 2020). If the transformative transportation technologies are used to substitute public transit or other non-motorized modes (e.g., walking, biking), they won't reduce VMT nor improve urban mobility. Additionally, the co-existence of different shared micro-mobility and ride-hailing systems may also cause competition among each other. Replacing shared e-scooter or bike-sharing trips with ride-hailing trips may increase vehicle usage (Portland.gov, 2019). Different mode substitution patterns may lead to significantly different changes of vehicle usage. Second, transformative transportation systems could be integrated with existing public transit systems to enable multimodal trips. If the transformative transportation systems help enhance public transit access by serving first-/last-mile trips, the multimodal trips could replace car trips and reduce VMT (Kong et al., 2020). Finally, transformative technologies may also increase overall vehicle usage in a city. For example, shared micro-mobility system operators need to periodically reposition shared bikes or e-scooters to undersupplied areas using trucks or vans, and the VMT generated from the repositioning process may outweigh the VMT reduction from car trip substitution (Fishman et al., 2014). Additionally, the deadheading and detour mileage from ride-hailing services could also increase overall vehicle usage and VMT, causing more traffic and transportation emissions (Tirachini & Gomez-Lobo, 2020).

The net impact of transformative transportation technologies on vehicle uses and ownership considering the above-mentioned complex interactions among the different systems has not yet been fully studied. The existing studies have two major limitations when assessing the impact of transformative transportation technologies on vehicle usage: (1) ignoring the integration of transformative transportation technologies and public transit system and the corresponding impacts on vehicle usage; and (2) overlooking the additional VMT that transformative transportation technologies may cause. In addition, the existing studies only investigated the vehicle usage impacts using historical data, which can only provide information based on the current transformative transportation technology adoption. However, the rapid expansion and development of different transformative transportation systems may significantly change individual travel behavior in the near future due to their increased service availability and reduced cost, and lead to various impacts on travel demand, traffic congestion, and air pollution (Shaheen & Cohen, 2018). The decision-makers and city planners currently lack tools to analyze the vehicle usage impacts from future transformative transportation technologies development scenarios, which is important to support policy and decision making.

To address this gap, this study developed an Integrated Traditional and Transformative Transportation System Use Model to evaluate how mode choice and vehicle usage may change under different development scenarios of transformative transportation technologies. The model considers both potential competition and integration among different traditional and transformative transportation systems. Indianapolis, IN is used as the case study city to develop and validate the model. The modeling framework can also be applied to other cities to obtain city-specific results.

7.2 Integrated Traditional and Transformative Transportation System Use Model

The agent-based Integrated Traditional and Transformative Transportation System Use Model simulates the travel behavior and vehicle usage changes for different transformative technology development scenarios. An agent-based model (ABM) is a bottom-up modeling approach that has been used in many research fields, including transportation (Heath et al., 2009). In an ABM, a complex adaptive system is simulated as a collection of agents, who can autonomously make decisions based on a set of rules. Agents may execute various actions that are appropriate for the system they represent. ABM simulates repetitive interactions between agents, allows agents to evolve, and explores the emergent dynamics of the real-world system (De Marchi & Page, 2014). Even a simple model can exhibit complex behavior patterns and provide valuable information about the dynamics of the real-world system that it emulates. ABM has the advantages of considering the transportation networks, heterogeneous individual demands and preferences, and complex system interactions in the model and has been increasingly used to study transformative transportation systems (Lokhandwala & Cai, 2018; Marczuk et al., 2016; Shaheen, 2012).

7.2.1 Data and Method

Figure 7.1 shows an overview of the modeling framework, which includes four major steps: (a) agent creation and initialization; (b) scenario design; (c) simulation running, and (d) output analysis. This section introduces the details of each step in the context of the case study city— Indianapolis, IN.

7.2.1.1 Agent creation and key assumptions. The model includes the following two types of agents: household agents and transportation agents.

7.2.1.1.1 Household agent and travel demand. For generating the household agents and their corresponding travel demands, we adopted the model developed by Wen et al. (2020), which generates a synthetic population and trip chains at the household level. Figure 7.2 shows the overview of the algorithm.

In our simulation model, each household agent represents one household, and is defined by a series of household information (e.g., household income, household size, worker count, driver count, etc.), and the socio-demographic attributes of each household member (age, gender, education, income, employment status, driver's license, etc.). A total of 372,000 household agents are generated based on Marion County population and the household characteristics are sampled from 2018 American Community Survey (ACS) based on the households in Marion County to ensure that the households we generated are representative (U.S. Census Bureau, 2019).

In addition, each household member is also assigned a group of utility functions to represent the travel behavior and mode choice pattern, given different transportation modes and trip purposes. In Chapter 5.2.3.2, we used MNL to quantify utility functions for Indianapolis residents' mode choice and the results are used here for each household member to make mode choice decisions. Each household member has two sets of utility functions (one for commuting trips and one for recreational trips), and the coefficients of the utility functions are also based on their socio-demographic attributes. In the simulation, each household member chooses the transportation mode that has the maximum utility to serve the trip demand.

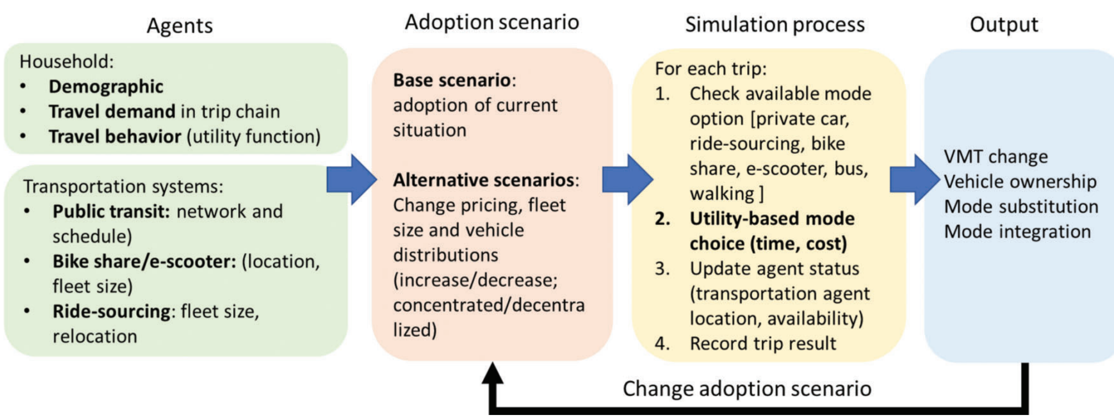


Figure 7.1 Modeling framework of the integrated traditional and transformative transportation system use model.

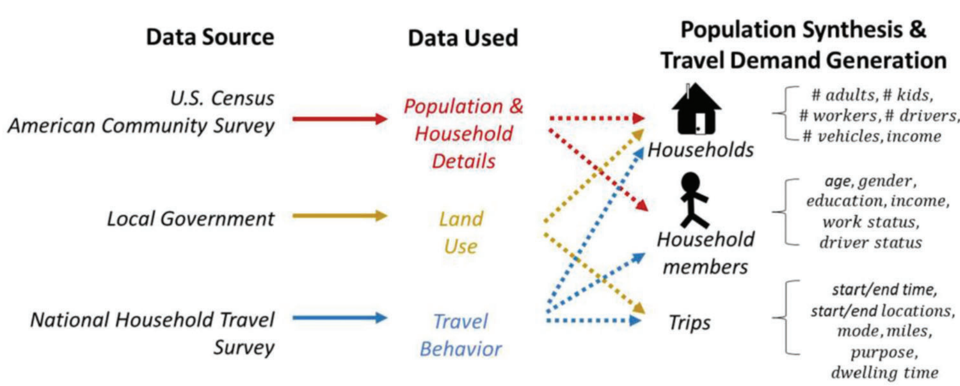


Figure 7.2 Overview of household agent and trip chain generation (Wen et al., 2020).

The travel demands are generated for each household member as a chain of trips, based on National Household Travel Survey (NHTS) data. NHTS data includes trip start and end time, travel mode (public transit, private vehicle, and walk), trip distance, purpose, etc. and also reports socio-demographic attributes of the surveyed households. Given that travel demand is correlated with household socio-demographic attributes, for each generated household agent, we sampled trip chains from the households in NHTS that share similar socio-demographic attributes in Marion County, IN (Wen et al., 2020). Because NHTS data does not contain trip spatial information, land use data (City of Indianapolis and Marion County, 2022) is used to further generate geolocations of trip origins/destinations (OD) and household home locations. The trip ODs and home locations are selected to ensure consistency among trip purpose, land use type, and trip distance. For example, a 10-mile home-based-work (HBW) trip should have a trip origin located in residential areas and trip destination located in a business area with a road distance of 10 miles between the two. More details of the location assignment process can be found in (Wen et al., 2020). The travel demand model of outputs for each household agent are the trip chain for each member with the information of trip OD location, start/end time, trip distance, trip purpose, and travel model. The travel mode sampled from NHTS doesn't include transformative transportation technologies, which can be used to represent the vehicle usage before launching these transformative systems. This study then used the generated trip chain as the input of the Integrated Traditional and Transformative Transportation System Use Model to simulate the mode choice and fleet operation based on the interaction between the household agents and the transportation agents which are introduced the next.

7.2.1.1.2 Transportation agents. The transportation agents include bike-sharing agents, shared e-scooter agents, and ride-hailing agents, representing transformative transportation systems. Private vehicles, public transit, and walk are also included in the simulation as available transportation modes based on input data.

Each bike-sharing agent represents one bike-sharing station, with the information of geolocation (e.g., longitude, latitude), station capacity (i.e., the number of docks), and the number of available bikes. When the selected mode choice of a trip includes bike-sharing (e.g., bike-sharing only or "bus + bike-sharing"), the number of available bikes at the origin station decreases by one at the trip start time (i.e., a bike is reserved and becomes unavailable) and the number of available bikes at the destination station will increase by one at the estimated arrival time. The number of available docks will also change accordingly.

Each shared e-scooter agent represents one shared e-scooter, with the information of geolocation (updated in real time during the simulation), availability status (i.e., in-service, reserved, idle, or out-of-battery), and battery level. When the selected mode choice of a trip includes shared e-scooter (e.g., e-scooter only or "bus + shared e-scooter"), the e-scooter will become reserved immediately at the trip start time. When the simulation reaches the estimated arrival time, the e-scooter will become available again, and the location will be updated to be the destination location. The battery level will also be decreased based on the trip distance served (the fully charged battery is 0.23 kWh and consumes energy at a rate of 0.015 kWh/mile). If the battery level is below 10%, the e-scooter will be out-of-battery and become unavailable.

Each ride-hailing agent represents one ride-hailing vehicle, with the information of geolocation (updated in real-time during the simulation), vehicle status (i.e., waiting, rebalancing, reserved, in-service, shift-out). Each ride-hailing vehicle will be assigned 10 candidate rebalancing locations based on the spatial kernel density function of travel demand, indicating that each driver has experience on where to head to for seeking the next passenger (Lokhandwala & Cai, 2018). When the vehicle drops off a passenger or waits at a rebalancing location for over 5 minutes, the vehicle will relocate to the next candidate location. The vehicle is still available during the rebalancing. When the selected mode choice of a trip includes ride-hailing (e.g., ride-hailing only or *bus + ride-hailing*), the vehicle will become reserved immediately at the trip start time and start heading to the pick-up location. After picking up the passenger, the vehicle will be in in-service status until the estimated arrival time. The ride-hailing vehicle is not allowed to share rides in our simulation. Each vehicle will also be assigned a shift-in and shift-out schedule, with the on-duty time ranges from 2 to 8 hours, to represent the intermittent availability of ride-hailing vehicles.

7.2.1.2 Simulation

7.2.1.2.1 Initialization. Before running the simulation, the model will first run the initialization to load all input data and create all agents that we introduced above. We chose 12:00:00 am on 10/02/2019 as the simulation start time and run 24 hours to represent a typical day. The initialization steps are the following.

1. Load OpenStreetMap (OSM) of Marion County area with road network (OpenStreetMap Contributors, n.d.).
2. Load GTFS data of IndyGo with the transit network and schedule information (Google, 2020).
3. Load ACS, NHTS, and land use data of Marion County (City of Indianapolis and Marion County, 2022; FHWA, 2018; U.S. Census Bureau, 2018).
4. Create 372,000 household agents to represent all households in Marion County. Each household member will be assigned a chain of trip demand with detailed spatial and temporal information, a group of utility functions to represent mode choice, and socio-demographic information based on the household and travel demand generation method from (Wen et al., 2020).

TABLE 7.1
Scenario settings

	Transformative Transportation Technologies	
	Availability	Cost
Base Scenario	0%	0%
Current Scenario	100%	100%
Alternative Scenarios (ratio to the current scenario)	[100%, 200%, 300%, 400%, 500%, 600%]	[100%, 80%, 60%, 40%, 20%, 10%]

5. Create bike-sharing agents. The number of stations, station distribution, capacity of each station, and the initial number of available bikes are based on the current system setting of Pacers bike share system in Indianapolis (Chapter 3.1). For the alternative scenarios (see Table 7.1), the new stations to be installed will follow the same spatial density function of the current system, as well as for the capacity and initial bikes. In the initialization phase, all bikes are available to use.
6. Create shared e-scooter agents. The number of shared e-scooters is based on scenario design (Table 7.1). The initial spatial distribution of e-scooters follows the same spatial density function of the current Bird and Lime systems in Indianapolis, based on our collected historical data (Chapter 3.1). At the beginning of the simulation, all e-scooters are available and fully charged.
7. Create ride-hailing agents. The number of ride-hailing vehicles is also based on the scenario. Each vehicle/driver will be assigned (1) 10 candidate rebalancing locations; (2) shift-in and shift-out schedule; and (3) initial location. The candidate rebalancing places and initial locations are generated based on the spatial kernel density of generated trip demands from household agents, indicating that drivers prefer to start their service or relocate to places with higher travel demands. The shift-in and shift-out schedule is solved using a classical scheduling optimization problem (Karger et al., 2009), to ensure that the number of on-duty vehicles follows the temporal distribution of trip demand while minimizing the total on-duty hours.

7.2.1.2.2 Running the simulation and the mode choice process. After loading all necessary data and creating all agents, the simulation will start to run for 24 hours (model time) with 1-minute time step. At each time step, the simulation model first updates the attributes of all agents (e.g., location, availability, battery level, etc.). Then, the model will load each trip that starts within the time step and run the matching process to simulate mode choice.

For each trip starting in the time step, the model will first check the available travel modes for the household member, considering the member's car ownership, walking distance, waiting time, travel cost, etc., and evaluate the time and monetary cost for using different transportation modes (including multimodal trips such as shared micro-mobility with transit) to serve the travel demands. If the assessed trip is a commuting trip, the alternative modes include private vehicle, ride-hailing, bus (walking as the connection trip), bus + bike-sharing, bus + shared e-scooter, and bus + ride-hailing, which are consistent with the options in the Indianapolis survey. If the assessed trip is a recreational trip (all non-commuting trips are considered as recreational trips in this study), the alternative modes include private vehicle, ride-hailing, bus (walking as the connection trip), bike-sharing, shared e-scooter, and ride-hailing. For each alternative mode (if applicable), the simulation will apply Open Trip Planner (OTP) to plan the fastest route for each mode and calculate the cost, in-vehicle time, and out-vehicle time (Morgan et al., 2019). The main assumptions include the following.

1. The average vehicle speed is 45 mph; the average walking speed is 2.5 mph; and the average speed of bike and e-scooter is 9 mph (based on the same setting in the Indianapolis survey). The in-vehicle time for each mode is calculated based on the in-vehicle distance and corresponding average travel speed. In-vehicle time for a bus trip is based on the boarding/alighting schedule of the matched bus trip.
2. A 3-minute out-vehicle time is applied to each private vehicle trip as the walking time to pick up vehicles, which is consistent with our mode choice survey setting (Chapter 5.2.1.4). Out-vehicle time for bus trips includes the walking time to/from the bus stop and the waiting time (including transfer time if applicable). Only the fastest bus trip (based on total trip duration) will be considered as the candidate trip. Out-vehicle time for walking-only trip is zero. Out-vehicle time for bike-sharing and shared e-scooter trips includes the walking time to access bikes/e-scooters. We assumed that the rider would pick up the closest bike/e-scooter as their choice and drop them off at the closest stations/locations. Out-vehicle time for ride-hailing trips includes the time waiting to be picked up by the matched vehicle. Only the closest available ride-hailing vehicle will be matched to pick up the rider.
3. The average private vehicle cost is $0.5/mile, and the bus cost is $1.4/trip, based on the setting from the Indianapolis survey (Chapter 5.2.1.4). Walking assumes to have zero monetary cost. Cost for transformative technologies vary based on scenario settings (Chapter 7.2.1.3).

With the necessary information obtained for each trip with each available mode, the mode choice decision will be made based on the utility functions of the traveler (generated household member). The mode with the maximum utility will be chosen as the selected mode choice. After choosing the travel mode, the attributes of selected vehicles (e.g., availability, location) will be changed accordingly. If the household member chooses bike-sharing or shared e-scooter (either using it for the entire trip or for transit connection), the selected shared bike or e-scooter will become unavailable until it is dropped off by the user. The available docks and bikes at the pick-up and drop-off bike-sharing stations, as well as the shared e-scooter's remaining battery energy level will be changed accordingly. If the household member chooses ride-hailing, a new sequence of pick-up/drop-off points, as well as the shortest vehicle route will be scheduled. After serving the trip (empty vehicle), the vehicle will be dispatched to candidate places with higher demands until being matched with the next passenger or shifted-out, similar to the approach used in (Lokhandwala & Cai, 2018).

7.2.1.3 Parameter setting and scenario design. In this study, we changed the availability and cost of transformative transportation technologies to simulate different development scenarios and analyze their impacts on vehicle usage and ownership. The scenario setting is shown in Table 7.1.

The *base scenario* represents that the system only has traditional transportation modes. This scenario is to represent the travel demand and vehicle usage before transformative technologies were launched in the city. It can also serve as the basis to calibrate and validate our simulation model, in which the mode choice and travel pattern should be similar with data in NHTS.

The *current scenario* shows the current service availability and pricing of transformative technologies in Indianapolis. The fleet size and the fleet distribution of bike-sharing and shared e-scooter systems are based on the current system (as discussed in Chapter 3.1). The fleet size of ride-hailing system is based on literature or operators' report. The vehicle repositioning rules could follow predetermined criteria (e.g., based on population density or travel demand density) or use the reposition optimization framework (Haliem et al., 2021; Lokhandwala & Cai, 2018; Yang et al., 2020). Table 7.2 lists the detailed settings of availability and cost for bike-sharing, shared e-sooter, and ride-hailing, based on the data and information we collected in Task 1. The *current scenario* can help understand how the current transformative technologies are affecting vehicle usage and ownership.

The *alternative scenarios* is a series of scenarios that varies the availability and cost using the *current scenario* as the basis. The hypothesis is that the availability of transformative transportation technologies may increase, and the cost may decrease with future development. We can use the *alternative scenarios* to simulate future adoption situations and analyze how the continuous development of transformative transportation technologies could change private vehicle usage and ownership at the city-level.

7.3 Model Validation

7.3.1 Household Validation

We first validated the household and trip generation algorithm with the spatial distribution of the generated households. Figure 7.3 shows the spatial distributions of household locations of ACS (U.S. Census Bureau, 2018) and the generated households in Marion County, Indiana. The color shows the household proportion (%) at the census track level. Two figures share similar patterns, indicating that the spatial distribution of generated households is representative of the households in Marion County. Because the socio-demographic patterns of each household and each household member are directly sampled from ACS, the distributions are guaranteed to be the same as the data in ACS.

7.3.2 Simulation Validation

We also assessed the simulation setting to make sure that the simulation can appropriately reflect people's historical travel behavior and mode choice when the transformative transportation technologies are not yet available. In the *base scenario*, the transportation modes should be consistent with the 2017 NHTS trip data. Figure 7.4 compares the mode share contributions of trips from 2017 NHTS data in Marion County and the simulated mode choice in the *base scenario*. As shown in the figure, the mode split is similar, indicating that the agents' settings are valid, and the multinomial logit (MNL) choice model (Chapter 5.2.3.2) can properly capture the travel behaviors and represent the mode choice of Indianapolis residents.

TABLE 7.2
Availability and cost settings for the current scenario

	Transformative Transportation Technologies	
	Availability	**Cost**
Bike-Sharing	50 stations with 525 bikes[1]	\$1 + \$0.15/min
Shared E-Scooter	3,000 shared e-scooters[1]	\$1 + \$0.32/min
Ride-Hailing	2,600 vehicles[2]	\$3.98 + \$0.16/min + \$0.87/mile

[1]Availability setting based on collected historical data (Chapter 3.1).
[2]Equal proportion of ride-hailing vehicle per thousand population with other cities (NYC Taxi and Limousine Commission, 2020).

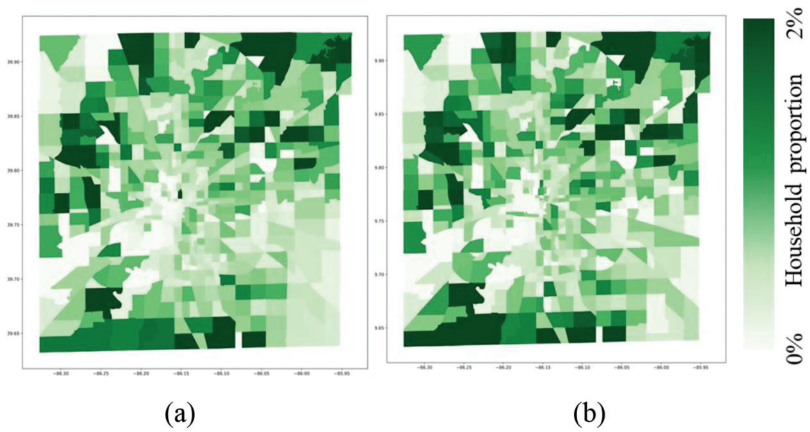


Figure 7.3 Spatial distribution of households at the census track level: (a) based on ACS 2018 data, and (b) generated by the model.

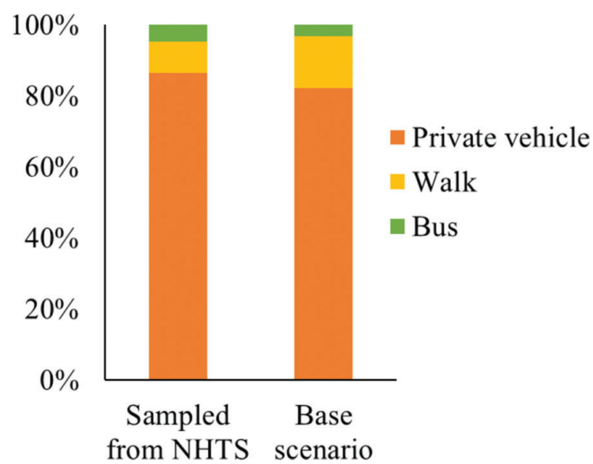


Figure 7.4 Mode split of trips from NHTS data and those simulated in the base scenario.

7.4 Transformative Transportation Technology Impact on Vehicle Usage and Car Ownership

7.4.1 Existing Transformative Transportation System (Current Scenario)

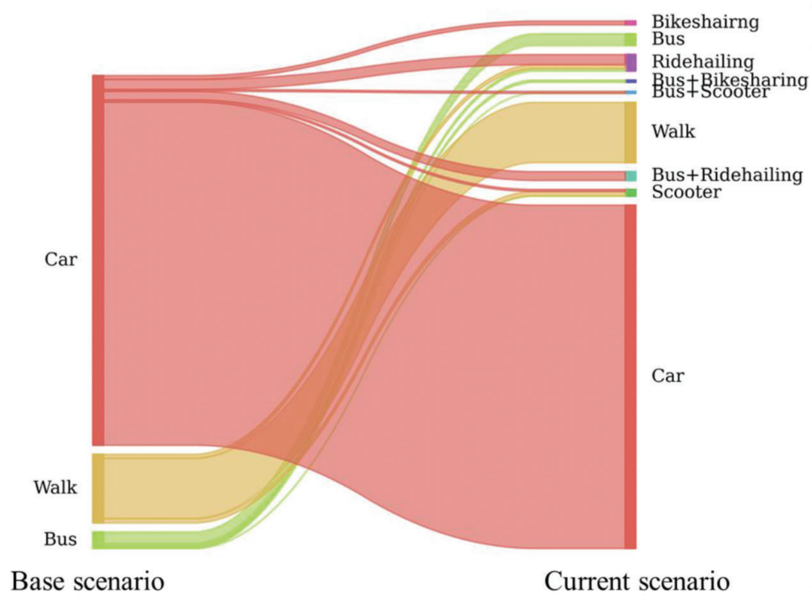
Figure 7.5a, b shows the mode shift pattern and the vehicle mileage change from the *base scenario* to the *current scenario*, respectively. Currently, the existing adoption of transformative transportation system does not reduce private vehicle usage in Indianapolis. Only a few private vehicle trips were shifted to ride-hailing. Shared micro-mobility, even integrated with transit system, still shows low probability to replace car trips, which is consistent with the findings in Chapter 5.3. People are more likely to use transformative transportation technologies to replace bus or walking trips. Multimodal usage is mainly to replace the walking effort of bus connection for existing bus riders. The current transformative transportation systems have limited capability to reduce private vehicle usage.

Due to the limited mode shift pattern, the current transformative technology may even increase the city-level VMT by 1.8% (VMT is contributed by both private vehicles and ride-hailing vehicles), worsening the traffic congestion and air pollution issues. Based on the daily VMT of passenger vehicles in Marion County (30,314,000 miles, estimated using the 2019 annual average daily traffic (AADT) data (INDOT, 2020)), the daily VMT increase due to the current transformative transportation technology is about 545,652 miles. These additional VMT could increase the daily fuel consumption by about 21,904 gallons (estimated based on an average fuel economy of 24.91 mpg (U.S. EPA, 2021)). Figure 7.5b shows the VMT composition of different modes, as well as the reduction benefits from shifting to other modes. Although the integration of shared micromobility and public transit offers some VMT reduction benefits, such benefits are outweighed by the VMT increase from ride-hailing. If a private vehicle trip is replaced by ride-hailing, the vehicle mileage cannot be reduced because the VMT to serve this trip is the same while the ride-hailing vehicle needs additional deadhead mileage to search for and pick up the passenger. The rebalancing and deadheading increase the city-level VMT.

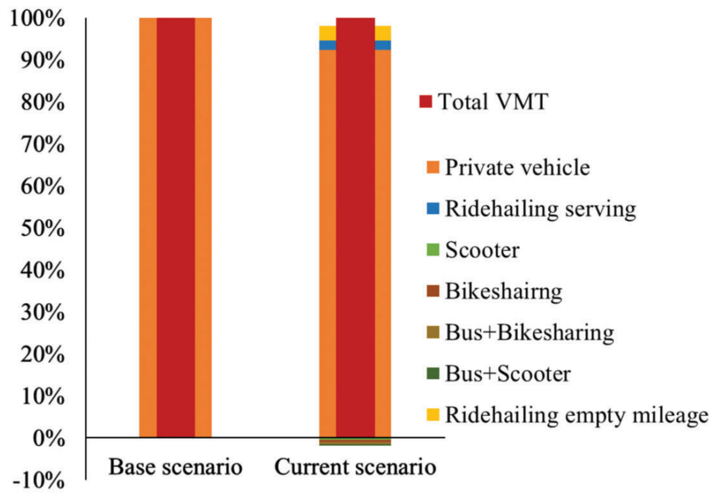
Based on the mode shift and VMT results, the current transformative technologies in Indianapolis did not play a significant role in replacing private vehicle use. Due to the limited mode shift, it is unlikely that car ownership would be reduced because of transformative technologies. Although about 2% of people claimed that their main commuting mode is transformative technology based on our Indianapolis survey results, people still cannot fully rely on transformative technologies and public transit to cover all types of travel demands.

7.4.2 Future Development Scenarios

Results from the *current scenario* show that the existing adoption of transformative technologies cannot reduce city-level vehicle usage. With the rapid development of transformative technologies, their availability and cost may be significantly changed and affect



(a)



(b)

Figure 7.5 Comparison between base scenario and current scenario in terms of (a) mode shift, and (b) VMT change.

people's mode choice. We ran different alternative development scenarios to analyze how different availability and cost of transformative transportation technology could change the overall VMT (including private vehicle ride-hailing vehicle mileage) for Indianapolis.

Figure 7.6a shows the VMT change under different shared micro-mobility development scenarios when ride-hailing keeps its current status. The cost of shared micro-mobility plays an important role in city-level VMT change. When the cost is dropped by 60% of its current level, the VMT replaced by shared micro-mobility can be breakeven with the VMT increase from ride-hailing. Further decreasing the cost can bring up to a 2% net VMT reduction when the availability (e.g., the number of shared bikes/e-scooters) is 600% of their current level. But expanding the system and increasing the number of shared vehicles may also cause other issues, such as sidewalk crowding, intensive rebalancing, power consumption for battery charging, etc. Integrating the system expansion and fare reduction can better encourage mode shift from private vehicle to micro-mobility.

Figure 7.6b shows the VMT change under different ride-hailing development scenarios when shared micro-mobility is kept at its current level. Increasing the ride-

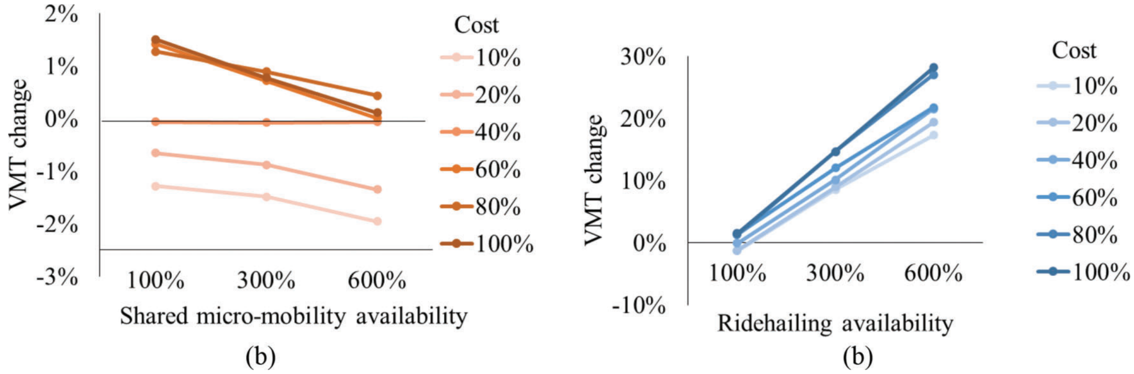


Figure 7.6 Total vehicle-miles-travelled compared with the base scenario in different alternative scenarios. (a) Shared micro-mobility development scenarios where ride-hailing keeps its current status, and (b) ride-hailing development scenarios where shared micro-mobility keeps its current status.

hailing availability may significantly increase the city's total VMT, bringing traffic congestion and air pollution. Although many private vehicle trips can be shifted to ride-hailing and reduce the VMT from private vehicles, the deadheading and rebalancing of ride-hailing vehicles can cause additional VMT. Only two scenarios with 100% availability and 10%~20% cost can obtain a net VMT reduction, thanks to the higher demand and as a result, improved system efficiency. In general, promoting ride-hailing service by itself cannot achieve VMT reduction benefits.

7.5 Chapter Summary

In this chapter, we proposed an agent-based Integrated Traditional and Transformative Transportation System Use Model to simulate the VMT and car ownership change under different development scenarios of transformative transportation technologies. Results from Indianapolis show that the current adoption of transformative transportation technology does not have a significant impact on vehicle usage and car ownership reduction. Transformative transportation technologies can only cover a small proportion of travel demand for a certain group of people. Limited trips can be shifted from private vehicles to other modes. Future development of transformative systems needs careful design to achieve benefits from reducing vehicle usage and car ownership. System expansion and fare reduction of shared micro-mobility show good potential to reduce the city-level VMT, while the development of a ride-hailing system is likely to increase total VMT due to deadheading and rebalancing needs.

The simulation model and scenario analysis results can help the Indiana Metropolitan Planning Organizations (MPOs) to anticipate potential travel demand change due to future transformative transportation technology development and support their decision-making. We chose Indianapolis as the case study city because of data availability for transformative transportation technologies. The model can be readily applied to other cities if the required data are available.

8. DISCUSSION AND CONCLUSIONS

8.1 Key Findings

This project evaluated the availability, use, and impact of transformative transportation technologies in Indiana cities using a diverse set of data sources and tools, such as historical trip data, survey, and simulation models. The key findings from this project are summarized below.

First, shared micro-mobility (i.e., bike-sharing and shared e-scooters) and ride-hailing services are the dominant transformative transportation technologies currently available in Indiana cities. Shared micro-mobility is mainly used for short trips, ranging from 0.8 to 1.2 miles. In general, shared e-scooter systems are much larger than bike-sharing systems in Indiana cities and are serving more trips, although at a higher cost. On average, each shared e-scooter can be used about three to four times per day, while each shared bike can only serve less than one trip per day. The system usage pattern also varies by city. As a transformative mode, shared micro-mobility is still in a rapid change in its type and service. Bike-sharing services in Greater Lafayette Area and Bloomington have been terminated, partially caused by the competition from the shared e-scooter system. E-bike adoption is rising in other cities, but we have not observed this change in Indiana cities yet. Ride-hailing use is more prevalent than both bike-sharing and shared e-scooters. The major user groups of shared micro-mobility and ride-hailing are different, based on results from the Indianapolis survey. In general, users of transformative transportation technology are mostly young adults (less than 44 years old). Most shared micro-mobility users are full-time workers, while ride-hailing users are more varied with a larger representation from retired and part-time workers. Males tend to use bike-sharing more but that's not the case for shared e-scooter and ride-hailing users. Older people tend to use ride-hailing more than other transformative transportation modes. The majority of shared e-scooters, bike-sharing, and ride-hailing users also own private vehicles.

Currently, transformative transportation technology has not affected car usage much but has decreased taxi and transit use. Results from the Indianapolis survey show that private vehicles are still the dominant choice when transformative transportation technology is available; and micro-mobility is replacing transit rather than complementing it. Further analysis of Indianapolis shared e-scooter trip records confirmed that most of the shared e-scooter trips in Indianapolis were likely to substitute walking trips or compete with the existing bus service. Trips that provided complementary service were mainly located outside of downtown, in the areas where the bus service is limited. Both survey and trip data analysis results show that very few users use shared micro-mobility to serve the first-/last-mile trips to connect to/from bus stops to make multimodal trips. The current reposition strategy, which redistributes most shared e-scooters to downtown, also encourages short trips that are likely to replace walking or compete with the bus service. Although shared micro-mobility has the potential to complement the bus system and improve urban mobility and transportation sustainability, the system operation and regulation need to be carefully designed to achieve the benefit.

The continuous development of transformative transportation technologies, in terms of improved service availability and reduced price, is anticipated to impact private vehicle use and overall VMT. Mode choice behavior based on the Indianapolis survey shows that, for short recreational trips, when the service availability increases and price reduces, there is a 10% probability that people will shift from private vehicle to transformative technologies. For commuting trips, it is more challenging to shift private vehicle use to multimodality. Multinomial logit (MNL) models show that travel cost is the key factor affecting people's mode choice decisions. The simulation results further show that increased shared micro-mobility adoption can help reduce overall VMT use by up to 2%; while higher provision of ride hailing services could increase the total VMT by up to 30% due to deadheading and rebalancing. In the near term, it is unlikely that car ownership will decrease due to these transformative technologies, because they cannot fully meet the diversity in travel demand.

The team recognized the need for detailed trip data to effectively assess the performance and impact of transformative transportation technologies. However, data availability varies significantly in different cities as well as by system type. In general, cities have more data and information for the shared micro-mobility systems than for ride-hailing services. Trip-level data can effectively support spatiotemporal analysis of system usage and provide invaluable information for system planning and policy making. However, trip-level data for Lafayette and Bloomington's shared e-scooter systems, as well as Indianapolis' bike-sharing system were not available at the time of this study. The availability of robust and easily accessible data pertaining to transportation modes and travel behaviors is essential for evaluating transformative transportation technologies in view of key performance indicators.

Based on a comprehensive literature review, the team concluded that the transformative transportation technologies should be evaluated based on operations, environmental, health and safety, and accessibility and equity metrics. Operations KPI includes fleet size, usage rate, trip demand, and mode integration, which helps to understand the system usage, supply-demand relation, and relationship with other transportation modes. The *Accessibility and Equity* KPI category measures the social justice issue, including the user demographics, spatial coverage, and connection to other transportation systems.

This study also provided a summary of literature on the impact of COVID-19 on traditional and transformative transportation system usage. The beginning stage of the COVID-19 pandemic resulted in a tremendous decrease in private vehicle and transit use and an increase in walking and cycling nationwide. During this time, travel to outdoor spaces and grocery stores decreased slightly; trips to recreational venues, places of work, and transit stations declined significantly. Time spent in residential locations increased slightly. As of May 2021, transit use has regained some of its popularity but not as much as pre-pandemic levels. Trips to residences, grocery stores, and recreational venues have almost achieved pre-pandemic levels, while trips to workplaces and transit stations are still significantly less popular destinations compared to pre-pandemic time. Outdoor spaces are significantly more popular than they were prior to the pandemic.

The Indianapolis survey confirmed these trends. Walking increased during COVID-19. Those who make mode transfers reported more dependency on walking to connect to other modes during the pandemic. While the overall trip frequency dropped, the choice of travel modes was affected differently. Dependency on walking and cars increased whereas the usage of all the other modes dropped. There was a change in frequency regarding all trip purposes. However, the change in work trips was not as significant as the change in other trip purposes such as shopping, personal, and social trips. The survey results further showed that, due to COVID-19, health is now perceived as extremely important when considering a work trip by the majority. People perceive the probability of contracting COVID-19 to be the highest for concurrently used transportation modes such as ride-hailing, taxis, and transit. They think the risk is lower for shared e-scooters and bike-sharing. The cost of a trip has also become more important after COVID-19.

8.2 Implementation Plan

The following recommendations are derived from the findings of this project.

First, dynamically monitoring and assessing the performance of transformative transportation systems is necessary to guide policy and investment decisions. Because of their transformative nature, transformative transportation systems may change rapidly. Timely information about system usage and performance is needed to effectively support decision-making for regulation and infrastructure development. While many cities have made open data a standard practice for transformative transportation systems, many Indiana cities still lack data.

Second, better integration between the transformative transportation systems and the existing transportation systems needs to be promoted. Currently, shared micro-mobility has rarely been used for transit connection in Indiana, partially due to the concentrated distribution of the shared fleets in the downtown area. Better integrating these systems can enable multimodal trips and improve urban mobility and transportation sustainability but will require integrated trip planning, payment, and fleet management.

Third, the results from the agent-based *Integrated Traditional and Transformative Transportation System Use Model* (Chapter 7) can help Indiana MPOs adjust the travel demand model and account for the impact of the transformative transportation technologies. For other cities, the developed modeling framework can also be applied to generate city-specific results. The models that we have developed for this project (system usage model in Chapter 3, competing/complementing relationship model in Chapter 6, and the agent-based simulation in Chapter 7) are available to analyze transformative transportation systems in additional Indiana cities or update the results for the current case study cities as more data becomes available. Results from this project can also inform future long-range transportation plan updates and provide useful information to the Multimodal Transit Team for their annual state transit reports.

REFERENCES

AAA. (2019). *Your driving costs: How much are you really paying to drive?* American Automobile Association. https://exchange.aaa.com/wp-content/uploads/2019/09/AAA-Your-Driving-Costs-2019.pdf

Abdullah, M., Dias, C., Muley, D., & Shahin, M. (2020). Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transportation Research Interdisciplinary Perspectives*, *8*, 100255. https://doi.org/10.1016/j.trip.2020.100255

Anderson, D. N. (2014). “Not just a taxi”? For-profit ridesharing, driver strategies, and VMT. *Transportation*, *41*(5), 1099–1117. https://doi.org/10.1007/s11116-014-9531-8

Arendsen, J. (2019, August 15). *Shared mobility for the first and last mile: Exploring the willingness to share* [Master’s thesis, Delft University of Technology]. https://repository.tudelft.nl/islandora/object/uuid:9976ea22-07be-4674-b984-1a8f6563f0ee/datastream/OBJ/download

Arentze, T. A., & Molin, E. J. E. (2013). Travelers’ preferences in multimodal networks: Design and results of a comprehensive series of choice experiments. *Transportation Research Part A: Policy and Practice*, *58*, 15–28. https://doi.org/10.1016/j.tra.2013.10.005

Awad-Núñez, S., Julio, R., Gomez, J., Moya-Gómez, B., & González, J. S. (2021). Post-COVID-19 travel behaviour patterns: impact on the willingness to pay of users of public transport and shared mobility services in Spain. *European Transport Research Review*, *13*(20). https://doi.org/10.1186/s12544-021-00476-4

Baltimore City Department of Transportation. (2019, March). *Dockless vehicle pilot program: Evaluation report*. https://transportation.baltimorecity.gov/sites/default/files/Pilot%20evaluation%20report%20FINAL.pdf

Bangert, D. (2020, August 2020). Purdue invites Spin back, WL watching to see how shared scooters blend with COVID-19 caution. *Lafayette Journal & Courier*. https://www.jconline.com/story/news/2020/08/30/purdue-invites-spin-back-wl-watching-see-how-shared-scooters-blend-covid-19-caution/5631371002/

Beck, M. J., & Hensher, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia – The early days of easing restrictions. *Transport Policy*, *99*, 95–119. https://doi.org/10.1016/j.tranpol.2020.08.004

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand*. MIT Press.

Biemer, P. P., & Christ, S. L. (2008). Weighting survey data. In E. D. de Leeuw, J. J. Hox, and D. A. Dillman (Eds.), *International Handbook of Survey Methodology*. Routledge. https://doi.org/10.4324/9780203843123.ch17

Blazina, E. (2020, May 13). Port Authority surveys previous riders as it prepares to return some service Sunday. *Pittsburgh Post-Gazette*. https://www.post-gazette.com/news/transportation/2020/05/13/Port-Authority-survey-increase-service-Campos-Allegheny-County-COVID-19/stories/202005130135

Broderick, R. (2020, March 17). *Uber and Lyft have suspended Uber Pool and Shared rides due to the Coronavirus*. Buzzfeednews. https://www.buzzfeednews.com/article/ryanhatesthis/uber-suspends-uber-pool-due-to-coronavirus

Brown, T. C., Ajzen, I., & Hrubes, D. (2003). Further tests of entreaties to avoid hypothetical bias in referendum contingent valuation. *Journal of Environmental Economics and Management*, *46*(2), 353–361. https://doi.org/10.1016/S0095-0696(02)00041-4

CDC. (2021). *When you’ve been fully vaccinated.* Centers for Disease Control and Prevention. Retrieved March 1, 2021, from https://www.cdc.gov/coronavirus/2019-ncov/vaccines/fully-vaccinated.html

Chai, X., Guo, X., Xiao, J., & Jiang, J. (2021, February 11). Analysis of spatial-temporal behavior pattern of the share bike usage during COVID-19 pandemic in Beijing. *Physics and Society*. http://arxiv.org/abs/2004.12340

Chapin, C., & Roy, S. S. (2021, April 19). A spatial web application to explore the interactions between human mobility, government policies, and COVID-19 cases. *Journal of Geovisualization and Spatial Analysis*, *5*(12). https://doi.org/10.1007/s41651-021-00081-y

Chappell, B. (2021, May 11). *Uber and Lyft will give free rides to COVID-19 vaccination spots, White House says*. https://www.npr.org/sections/coronavirus-live-updates/2021/05/11/995882805/uber-and-lyft-will-give-free-rides-to-covid-19-vaccination-spots-white-house-say

Chicago Department of Transportation. (2020, January). *E-scooter pilot evaluation summary* (Issue January).

https://www.chicago.gov/content/dam/city/depts/cdot/Misc/EScooters/E-Scooter_Pilot_Evaluation_2.17.20.pdf

Ciccocioppo, B. (2021, May 4). *Wolf administration to lift mitigation orders on Memorial Day, masking order once 70% of Pennsylvania adults fully vaccinated*. Pennsylvania Pressroom. https://www.media.pa.gov/pages/health-details.aspx?newsid=1437

City of Austin Transportation Department. (2019). *Dockless mobility community survey report*. http://austintexas.gov/sites/default/files/files/Transportation/Dockless_Mobility_Community_Survey_Report_2-28-19.pdf

City of Indianapolis and Marion County. (2022, July 25). *Indianapolis and Marion County current land use. Indy GIS*. https://data.indy.gov/datasets/current-land-use/explore

Clewlow, R. R., & Mishra, G. S. (2017, October). *Disruptive transportation: The adoption, utilization, and impacts of ride-hailing in the United States* (Research Report – UCD-ITS-RR-17-07). http://www.reginaclewlow.com/pubs/2017_UCD-ITS-RR-17-07.pdf

Cochran, A. L. (2020). Impacts of COVID-19 on access to transportation for people with disabilities. *Transportation Research Interdisciplinary Perspectives*, *8*, 100263. https://doi.org/10.1016/j.trip.2020.100263

Combs, T. S., & Pardo, C. F. (2021). Shifting streets COVID-19 mobility data: Findings from a global dataset and a research agenda for transport planning and policy. *Transportation Research Interdisciplinary Perspectives*, *9*, 100322. https://doi.org/10.1016/j.trip.2021.100322

Cummings, R. G., Harrison, G. W., & Rutström, E. E. (1995, March). Homegrown values and hypothetical surveys: Is the dichotomous choice approach incentive-compatible? *American Economic Association*, *85*(1), 260–266 https://www.jstor.org/stable/pdf/2118008.pdf

Dai, J., Liu, Z., & Li, R. (2021). Improving the subway attraction for the post-COVID-19 era: The role of fare-free public transport policy. *Transport Policy*, *103*, 21–30. https://doi.org/10.1016/j.tranpol.2021.01.007

Dallas Area Rapid Transit. (2020, June 16). *DART to install COVID-19 shields on all buses*. https://www.masstransitmag.com/safety-security/safety-services-products/press-release/21142375/dallas-area-rapid-transit-dart-dart-to-install-covid19-shields-on-all-buses

De Marchi, S., & Page, S. E. (2014, May). Agent-based models. *Annual Review of Political Science*, *17*, 1–20. https://doi.org/10.1146/annurev-polisci-080812-191558

Dingil, A. E., & Esztergár-Kiss, D. (2021). The influence of the Covid-19 pandemic on mobility patterns: The first wave's results. *Transportation Letters*, *13*(5–6). https://doi.org/10.1080/19427867.2021.1901011

Downtown Indy. (2021). *Parking meters*. https://downtownindy.org/parking/parking-meters

Dzisi, E. K., Jr., Obeng-Atuah, D., Ackaah, W., Tuffour, A. Y., & Aidoo, N. E. (2021). Uptake in on-demand ride-hailing for intracity long distance trip making during COVID-19. *Urban, Planning and Transport Research*, *9*(1), 1–12. https://doi.org/10.1080/21650020.2021.1872415

Escobari, M., Seyal, I., & Daboin, C. D. (2020, November 16). *New but narrow job pathways for America's unemployed and low-wage workers*. https://www.brookings.edu/blog/up-front/2020/11/16/new-but-narrow-job-pathways-for-americas-unemployed-and-low-wage-workers/

Fagnant, D. J., & Kockelman, K. M. (2015). Dynamic ride-sharing and optimal fleet sizing for a system of shared autonomous vehicles. *TRB 94th Annual Meeting Compendium of Papers*. Transportation Research Board.

Fan, Y., Guthrie, A., & Levinson, D. (2016). Waiting time perceptions at transit stops and stations: Effects of basic amenities, gender, and security. *Transportation Research Part A: Policy and Practice*, *88*, 251–264. https://doi.org/10.1016/j.tra.2016.04.012

FHWA. (2018). *KABCO injury classification scale and definitions*. Federal Highway Administration. https://safety.fhwa.dot.gov/hsip/spm/conversion_tbl/pdfs/kabco_ctable_by_state.pdf

Fishman, E., Washington, S., & Haworth, N. (2014). Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia. *Transportation Research Part D: Transport and Environment*, *31*, 13–20. https://doi.org/10.1016/j.trd.2014.05.013

Fumagalli, L. A. W., Rezende, D. A., & Guimarães, T. A. (2021). Challenges for public transportation: Consequences and possible alternatives for the Covid-19 pandemic through strategic digital city application. *Journal of Urban Management*, *10*(2), 97–109. https://doi.org/10.1016/j.jum.2021.04.002

Garaus, M., & Garaus, C. (2021). The impact of the Covid-19 pandemic on consumers' intention to use shared-mobility services in German cities. *Frontiers in Psychology*, *12*, 646593. https://doi.org/10.3389/fpsyg.2021.646593

Garvin, M., Molenaar, K. R., Navarro, D., & Proctor, G. (2011, March). *Key performance indicators in public-private partnerships*. http://permanent.access.gpo.gov/gpo11086/pl10029.pdf

Gkartzonikas, C., & Gkritza, K. (2019). What have we learned? A review of stated preference and choice studies on autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 323–337. https://doi.org/10.1016/j.trc.2018.12.003

Gkiotsalitis, K. (2021). A model for modifying the public transport service patterns to account for the imposed COVID-19 capacity. *Transportation Research Interdisciplinary Perspectives*, *9*, 100336. https://doi.org/10.1016/j.trip.2021.100336

Goldbaum, C. (2020). Why women are biking in record numbers in N.Y.C. *The New York Times*. https://www.nytimes.com/2020/10/07/nyregion/nyc-biking-covid-women.html

Google. (2020). *General transit feed specification* [Data set]. Google. Retrieved July 10, 2020, from https://developers.google.com/transit/gtfs/reference

Graber, A. (2020, June 8). *WI: The pandemic response slashed traffic; what did it teach us about transportation planning?* Wisconsin Public Transportation Association. https://wipta.wildapricot.org/news/9023198

Haghani, M., Bliemer, M. C. J., Rose, J. M., Oppewal, H., & Lancsar, E. (2021). *Hypothetical bias in stated choice experiments: Part I. Integrative synthesis of empirical evidence and conceptualisation of external validity*. https://arxiv.org/ftp/arxiv/papers/2102/2102.02940.pdf

Haliem, M., Mani, G., Aggarwal, V., & Bhargava, B. (2021, June 14). *A distributed model-free ride-sharing approach for joint matching, pricing, and dispatching using deep reinforcement learning*. http://arxiv.org/abs/2010.01755

Heath, B., Hill, R., & Ciarallo, F. W. (2009). A survey of agent-based modeling practices (January 1998 to July 2008). *Journal of Artificial Societies and Social Simulation*, *12*(4).

Henry, B. (2021, May 17). Electric bike share program coming to Encinitas. *San Diego Union-Tribune*. https://www.encinitasadvocate.com/news/story/2021-05-17/electric-bike-share-program-coming-to-encinitas

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis: A primer*. Cambridge University Press.

Ho, C. Q., Mulley, C., & Hensher, D. A. (2020). Public preferences for mobility as a service: Insights from stated preference surveys. *Transportation Research Part A: Policy and Practice*, *131*, 70–90. https://doi.org/10.1016/j.tra.2019.09.031

Hollingsworth, J., Copeland, B., & Johnson, J. X. (2019). Are e-scooters polluters? The environmental impacts of shared dockless electric scooters. *Environmental Research Letters*, *14*(8), 84031. https://doi.org/10.1088/1748-9326/ab2da8

Hu, S., & Chen, P. (2021). Who left riding transit? Examining socioeconomic disparities in the impact of COVID-19 on ridership. *Transportation Research Part D: Transport and Environment*, *90*, 102654. https://doi.org/10.1016/j.trd.2020.102654

Huang, J., Wang, H., Fan, M., Zhuo, A., Sun, Y., & Li, Y. (2020). Understanding the impact of the COVID-19 pandemic on transportation-related behaviors with human mobility data. *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 3443–3450. https://doi.org/10.1145/3394486.3412856

INDOT. (2020). *Indiana traffic statistics*. Indiana Department of Transportation. https://www.in.gov/indot/resources/traffic-data/

IndyGo. (n.d.). *Fares & passes* [Webpage]. Retrieved May 17, 2021, from https://www.indygo.net/fares-and-passes/

INRIX. (2017, July 12). *Searching for parking costs Americans $73 billion a year.* Retrieved from May 17, 2021, from https://www.prnewswire.com/news-releases/searching-for-parking-costs-americans-73-billion-a-year-300486543.html

Irawan, M. Z., Rizki, M., Joewono, T. B., & Belgiawan, P. F. (2020). Exploring the intention of out-of-home activities participation during new normal conditions in Indonesian cities. *Transportation Research Interdisciplinary Perspectives*, *8*, 100237. https://doi.org/10.1016/j.trip.2020.100237

Jacquemet, N., Joule, R.-V., Luchini, S., & Shogren, J. F. (2013). Preference elicitation under oath. *Journal of Environmental Economics and Management*, *65*(1), 110–132. https://doi.org/10.1016/j.jeem.2012.05.004

Jaggers, D. (2021, March 8). *Reflections: A timeline of the COVID-19 pandemic in Indiana. wfyi Indianapolis*. https://www.wfyi.org/news/articles/reflections-a-timeline-of-the-covid-19-pandemic-in-indiana

Jiao, J., & Azimian, A. (2021). Exploring the factors affecting travel behaviors during the second phase of the COVID-19 pandemic in the United States. *Transportation Letters: The International Journal of Transportation Research*, *13*(5–6), 331–343. https://doi.org/10.1080/19427867.2021.1904736

Jin, F., An, K., & Yao, E. (2020). Mode choice analysis in urban transport with shared battery electric vehicles: A stated-preference case study in Beijing, China. *Transportation Research Part A: Policy and Practice*, *133*, 95–108. https://doi.org/10.1016/j.tra.2020.01.009

Johnson, R., & Orme, B. (2003). *Getting the most from CBC*. Sawtooth Software Research Paper Series. https://sawtoothsoftware.com/resources/technical-papers/getting-the-most-from-cbc

Joshi, M., Cowan, N., Limone, O., Mcguinness, K., & Rao, R. (2019). *E-hail regulation in global cities*. https://wagner.nyu.edu/impact/research/publications/e-hail-regulation-global-cities

Karger, D., Stein, C., & Wein, J. (2009). *Scheduling algorithms*. Springer. https://dl.acm.org/doi/pdf/10.5555/1882723.1882743

Ke, J., Yang, H., & Zheng, Z. (2020). On ride-pooling and traffic congestion. *Transportation Research Part B: Methodological*, *142*, 213–231. https://doi.org/10.1016/j.trb.2020.10.003

Knoblauch, R. L., Pietrucha, M. T., & Nitzburg, M. (1996). Field studies of pedestrian walking speed and start-up time. *Transportation Research Record*, *1538*(1), 27–38. https://doi.org/10.1177/0361198196153800104

Kong, H., Jin, S. T., & Sui, D. Z. (2020). Deciphering the relationship between bikesharing and public transit: Modal substitution, integration, and complementation. *Transportation Research Part D: Transport and Environment*, *85*, 102392. https://doi.org/10.1016/j.trd.2020.102392

König, A., & Dreßler, A. (2021). A mixed-methods analysis of mobility behavior changes in the COVID-19 era in a rural case study. *European Transport Research Review*, *13*(15). https://doi.org/10.1186/s12544-021-00472-8

Lekach, S. (2020, May 6). *As cities reopen, Lyft rides slowly ramp up*. Mashable. https://mashable.com/article/lyft-earnings-increase-rides

Li, A., Zhao, P., He, H., & Axhausen, K. W. (2020). *Understanding the variations of micro-mobility behavior before and during COVID-19 pandemic period*. https://doi.org/10.3929/ethz-b-000430395

List, J. A., Sinha, P., & Taylor, M. H. (2006). Using choice experiments to value non-market goods and services: Evidence from field experiments. *Advances in Economic Analysis & Policy*, *6*(2). http://s3.amazonaws.com/fieldexperiments-papers2/papers/00278.pdf

Liu, Y., Bansal, P., Daziano, R., & Samaranayake, S. (2019). A framework to integrate mode choice in the design of mobility-on-demand systems. *Transportation Research Part C: Emerging Technologies*, *105*, 648–665. https://doi.org/10.1016/j.trc.2018.09.022

Lock, O. (2020, June 27). Cycling behaviour changes as a result of COVID-19: A survey of users in Sydney, Australia. *Transportation Findings*. https://doi.org/10.32866/001c.13405

Lokhandwala, M., & Cai, H. (2018). Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC. *Transportation Research Part C: Emerging Technologies*, *97*, 45–60. https://doi.org/10.1016/j.trc.2018.10.007

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2010). *Stated choice methods: Analysis and applications*. Cambridge University Press.

Luo, H., Zhang, Z., Gkritza, K., & Cai, H. (2021). Are shared electric scooters competing with buses? a case study in Indianapolis. *Transportation Research Part D: Transport and Environment*, *97*, 102877. https://doi.org/10.1016/j.trd.2021.102877

Ma, X., Zhang, X., Li, X., Wang, X., & Zhao, X. (2019). Impacts of free-floating bikesharing system on public transit ridership. *Transportation Research Part D: Transport and Environment*, *76*, 100–110. https://doi.org/10.1016/j.trd.2019.09.014

Marczuk, K. A., Soh, H. S. H., Azevedo, C. M. L., Lee, D.-H., & Frazzoli, E. (2016). Simulation framework for rebalancing of autonomous mobility on demand systems. *MATEC Web of Conferences*, *81*(2016), 01005. https://doi.org/10.1051/matecconf/20168101005

Martin, E. W., & Shaheen, S. A. (2014). Evaluating public transit modal shift dynamics in response to bikesharing: A tale of two U.S. cities. *Journal of Transport Geography*, *41*, 315–324. https://doi.org/10.1016/j.jtrangeo.2014.06.026

Mathew, J. K., Liu, M., & Bullock, D. M. (2019). Impact of weather on shared electric scooter utilization. *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, 2019, 4512–4516. https://doi.org/10.1109/ITSC.2019.8917121

McGuinness, J. (2019). *Indiana Department of Transportation 2019 strategic plan*. https://www.in.gov/indot/files/INDOTStrategicPlan.pdf

McQueen, M. G. (2020). *Comparing the promise and reality of e-scooters: A critical assessment of equity improvements and mode-shift* [Master's thesis, Portland State University]. PDXScholar. https://doi.org/10.15760/etd.7439

Mogaji, E. (2020). Impact of COVID-19 on transportation in Lagos, Nigeria. *Transportation Research Interdisciplinary Perspectives*, *6*, 100154. https://doi.org/10.1016/j.trip.2020.100154

Morgan, M., Young, M., Lovelace, R., & Hama, L. (2019). OpenTripPlanner for R. *Journal of Open Source Software*, *4*(44), 1926. https://doi.org/10.21105/joss.01926

MOVMI. (2018, November 26). *The Ridehailing trend: Past, present, and future overview of ridehailing*. www.movmi.net/blog/ridehailing-trend-overview/

Munawar, H. S., Khan, S. I., Qadir, Z., Kouzani, A. Z., & Mahmud, M. A. P. (2021). Insight into the impact of COVID-19 on Australian transportation sector: An economic and community-based perspective. *Sustainability*, *13*(3), 1276. https://doi.org/10.3390/su13031276

NABSA. (2020). *MobilityData/gbfs* [Webpage]. https://github.com/MobilityData/gbfs

NACTO. (2017). *Bike share in the U.S.: 2017*. National Association of City Transportation Officials. https://nacto.org/bike-share-statistics-2017/

NACTO. (2018). *Shared micromobility in the U.S.: 2018*. National Association of City Transportation Officials. https://nacto.org/shared-micromobility-2018/

NREL. (2019). *Measuring mobility potential*. National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy20osti/73579.pdf

NYC Taxi & Limousine Commission. (2020). Taxi and ridehailing usage in New York City. https://toddwschneider.com/dashboards/nyc-taxi-ridehailing-uber-lyft-data/

OpenStreetMap Contributors. (n.d.). *Planet OSM*. Retrieved from https://planet.osm.org

Orr, B., MacArthur, J., & Dill, J. (2019, February 1). The Portland e-scooter experience. In *TREC Friday Seminar Series* (Vol. 163). https://pdxscholar.library.pdx.edu/trec_seminar/163

Our World in Data. (2021). *How did the number of visitors change since the beginning of the pandemic?, United States*. https://ourworldindata.org/grapher/changes-visitors-covid?time=earliest..2020-09-22&country=~USA

Ozbilen, B., Slagle, K. M., & Akar, G. (2021). Perceived risk of infection while traveling during the COVID-19 pandemic: Insights from Columbus, OH. *Transportation Research Interdisciplinary Perspectives*, *10*, 100326. https://doi.org/10.1016/j.trip.2021.100326

Portland.gov. (2019). *2018 e-scooter findings report*. City of Portland, Oregon. https://www.portlandoregon.gov/transportation/article/709719%0Ahttps://trid.trb.org/view/1607260

Pula, K., Shinkle, D., & Rall, J. (2015, June). *On track: How states fund and support public transportation*. https://www.ncsl.org/Portals/1/Documents/transportation/ontrack.pdf

Rasca, S., Markvica, K., & Ivanschitz, B. P. (2021). Impacts of COVID-19 and pandemic control measures on public transport ridership in European urban areas – The cases of Vienna, Innsbruck, Oslo, and Agder. *Transportation Research Interdisciplinary Perspectives*, *10*, 100376. https://doi.org/10.1016/j.trip.2021.100376

Rayle, L., Shaheen, S., Chan, N., Dai, D., & Cervero, R. (2014). *App-based, on-demand ride services: Comparing taxi and ridesourcing trips and user characteristics in San Francisco*. https://www.its.dot.gov/itspac/dec2014/ridesourcingwhitepaper_nov2014.pdf

Saha, J., Barman, B., & Chouhan, P. (2020). Lockdown for COVID-19 and its impact on community mobility in India: An analysis of the COVID-19 community mobility reports, 2020. *Children and Youth Services Review*, *116*, 105160. https://doi.org/10.1016/j.childyouth.2020.105160

Scorrano, M., & Danielis, R. (2021). Active mobility in an Italian city: Mode choice determinants and attitudes before and during the Covid-19 emergency. *Research in Transportation Economics*, *86*, 101031. https://doi.org/10.1016/j.retrec.2021.101031

Shaheen, S. (2020). *Impacts of COVID-19 on shared mobility* [Webinar]. TRB Forum on COVID-19, AVs, and Shared Mobility. https://www.nationalacademies.org/event/05-13-2020/2020-forum-on-covid-19-avs-and-shared-mobility#sl-three-columns-ecf11326-a141-4a2a-a00f-379975bedab8

Shaheen, S. A. (2013). Introduction: Shared-use vehicle services for sustainable transportation: Carsharing, bikesharing, and personal vehicle sharing across the globe. *International Journal of Sustainable Transportation*, *7*(1), 1–4. https://doi.org/10.1080/15568318.2012.660095

Shaheen, S., Bell, C., Cohen, A., & Yelchuru, B. (2017, August). *Travel behavior: Shared mobility and transportation equity* (Report No. PL-18-007). Booz Allen Hamilton Inc. https://www.fhwa.dot.gov/policy/otps/shared_use_mobility_equity_final.pdf

Shaheen, S., & Cohen, A. (2018). Shared mobility policies for California. *ITS Berkeley Policy Briefs*, *2018*(3), 0–3. https://doi.org/10.7922/G2VX0DP9

Shaheen, S., & Cohen, A. (2019, April 1). *Shared micromoblity policy toolkit: Docked and dockless bike and scooter sharing*. UC Berkeley Transportation Sustainability Research Center. https://doi.org/10.7922/G2TH8JW7

Shaheen, S., Martin, E., & Cohen, A. (2013). Public bikesharing and modal shift behavior: A comparative study of early bikesharing systems in North America. *International Journal of Transportation*, *1*(1), 35–54. https://doi.org/10.14257/ijt.2013.1.1.03

Shaheen, S. A. (2012). Introduction: Shared-use vehicle services for sustainable transportation: Carsharing, bikesharing, and personal vehicle sharing across the globe. *International Journal of Sustainable Transportation*, *7*(1), 1–4. https://doi.org/10.1080/15568318.2012.660095

Shaheen, S. A., Martin, E. W., Chan, N. D., Cohen, A. P., & Pogodzinski, M. (2014, October). *Public bikesharing in North America during a period of rapid expansion: Understanding business models, industry trends, and user impacts* (MTI Report 12-29). Mineta Transportation Institute. https://transweb.sjsu.edu/sites/default/files/1131-public-bikesharing-business-models-trends-impacts.pdf

Shokouhyar, S., Shokoohyar, S., Sobhani, A., & Gorizi, A. J. (2021, April). Shared mobility in post-COVID era: New challenges and opportunities. *Sustainable Cities and Society*, *67*, 102714. https://doi.org/10.1016/j.scs.2021.102714

Smith, C. S., & Schwieterman, J. P. (2018). *E-scooter scenarios: Evaluating the potential mobility benefits of shared* *dockless scooters in Chicago*. https://www.researchgate.net/publication/330093998

Smith, M. (2019, December 3). *Here's how long you have to wait for an Uber or Lyft in DC*. WTOP news. Retrieved May 17, 2021, from https://wtop.com/dc-transit/2019/12/how-long-you-have-to-wait-for-an-uber-or-lyft-in-d-c/

Sy, K. T. L., Martinez, M. E., Rader, B., & White, L. F. (2020). Socioeconomic disparities in subway use and COVID-19 outcomes in New York City. *American Journal of Epidemiology*, *190*(7), 1234–1242. https://doi.org/10.1093/aje/kwaa277

Tan, L., & Ma, C. (2021, April). Choice behavior of commuters' rail transit mode during the COVID-19 pandemic based on logistic model. *Journal of Traffic and Transportation Engineering* (English Edition), *8*(2), 186–195. https://doi.org/10.1016/j.jtte.2020.07.002

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

Tirachini, A. (2020). Ride-hailing, travel behaviour and sustainable mobility: an international review. *Transportation*, *47*, 2011–2047. https://doi.org/10.1007/s11116-019-10070-2

Tirachini, A., & Cats, O. (2020). COVID-19 and public transportation: Current assessment, prospects, and research needs. *Journal of Public Transportation*, *22*(1), 1–34. https://doi.org/10.5038/2375-0901.22.1.1

Tirachini, A., & Gomez-Lobo, A. (2020). Does ride-hailing increase or decrease vehicle kilometers traveled (VKT)? A simulation approach for Santiago de Chile. *International Journal of Sustainable Transportation*, *14*(3), 187–204. https://doi.org/10.1080/15568318.2018.1539146

Uber. (2020, June 30). *How to disinfect your vehicle or food delivery equipment*. https://www.uber.com/newsroom/our-commitment-to-clean/

U.S. Census Bureau. (2018). *ACS 5-year estimates public use microdata sample* (American Community Survey, 2012-2016 ACS 5-year estimates). https://data.census.gov/mdat/#/search?ds=ACSPUMS5Y2016

U.S. Census Bureau. (2019). *2014-2018 American Community Survey 5-year public use microdata*.

U.S. EPA. (2021). *Explore the automotive trends report*. https://www.epa.gov/automotive-trends/explore-automotive-trends-data

Wang, H., & Noland, R. B. (2021). Bikeshare and subway ridership changes during the COVID-19 pandemic in New York City. *Transport Policy*, *106*, 262–270. https://doi.org/10.1016/j.tranpol.2021.04.004

Warren, M. S., & Skillman, S. W. (2020, March 31). *Mobility changes in response to COVID-19*. http://arxiv.org/abs/2003.14228

Washington, S., Karlaftis, M., Mannering, F., & Anastasopoulos, P. (2020). *Statistical and econometric methods for transportation data analysis* (3rd ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9780429244018

Wen, R., Jiang, Z., Liang, C., Telenko, C., Wang, B., Fu, Y., & Cai, H. (2020, April 14). A new approach of generating travel demands for smart transportation systems modeling. *SAE International*. https://doi.org/10.4271/2020-01-1047

White, A. A., Landis, J. R., & Cooper, M. M. (1982). A note on the equivalence of several marginal homogeneity test criteria for categorical data. *International Statistical Review / Revue Internationale de Statistique*, *50*(1), 27–34. https://doi.org/10.2307/1402457

Wu, C., Le Vine, S., Sivakumar, A., & Polak, J. (2019). Traveller preferences for free-floating carsharing vehicle allocation mechanisms. *Transportation Research Part C: Emerging Technologies*, *102*, 1–19. https://doi.org/10.1016/j.trc.2019.02.019

Yan, X., Levine, J., & Zhao, X. (2019). Integrating ridesourcing services with public transit: An evaluation of traveler responses combining revealed and stated preference data. *Transportation Research Part C: Emerging Technologies*, *105*, 683–696. https://doi.org/10.1016/j.trc.2018.07.029

Yang, H., Qin, X., Ke, J., & Ye, J. (2020). Optimizing matching time interval and matching radius in on-demand ride-sourcing markets. *Transportation Research Part B: Methodological*, *131*, 84–105. https://doi.org/10.1016/j.trb.2019.11.005

Yap, M. D., Correia, G., & van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A: Policy and Practice*, *94*, 1–16. https://doi.org/10.1016/j.tra.2016.09.003

APPENDICES

Appendix A. Greater Lafayette Survey

Appendix B. Indianapolis Survey

APPENDIX A. GREATER LAFAYETTE SURVEY

The following is the summary table of all questions in the Greater Lafayette survey.

Table A.1 Summary table of the Greater Lafayette survey

Question	Description	Response Frequency (%)
What methods of transportation is AVAILABLE to you on daily basis?	Private car/Private bike/Private motorcycle/Shared e-scooters/Shared bikes/Private e-scooter/Other	(33/17/2/19/20/2/8)
Which of the following transformative transportation technology have YOU USED in the past year?	Shared e-scooters/shared bikes/both/none	(26/12/15/47)
Which one do you use more frequently?	Shared e-scooters/shared bikes	(60/40)
Why haven't you used any shared e-scooters or shared bikes?	I'm planning to but haven't had the chance yet/It's too expensive/Don't know how to, Scared of riding, Do not feel safe/Don't have the app, phone to run the required app/They do not seem like an effective way to travel/No local shared e-scooter service around/No local bike service around/The distance I need to travel is too long to use them/The distance I need to travel is too short to use them/Other	(7/14/19/11/9/9/7/12/8/9)
Why did you choose to use shared e-scooters over shared bikes?	Bike-sharing is not available in my area/Shared e-scooter is cheaper than bike-sharing/More units of shared e-scooters available near me than shared bikes/Less physical work compared to riding a bike/e-scooter is faster than a bike/Riding an e-scooter is more fun than a shared bike/Other	(6/10/17/21/16/28/3)
Currently, how often do you use a shared e-scooter?	Rarely/Once a month/Once a week/Twice a week/3–5 Times a week/6+ times a week	(59/18/12/5/3/3)
What is the average distance of your shared e-scooter trips?	(<0.5 mile/0.5–1 miles/1–3 miles/3–10miles)	(13/49/30/7)
How often do you use shared e-scooters to access a bus/shuttle, Metro rail, or commuter rail?	(Never/1–2 times a year/1–2 times per quarter/1–2 times per month/3–5 times per month/Couple of times a week/Almost every day of the week)	(68/12/7/4/2/5/0)
What is the maximum price (in U.S. Dollars) that you are willing to pay for a recurring 1-mile trip using shared e-scooters (above that price you will switch to other modes of transportation)?	(Less than $1.00/$1.00–$1.50/$1.51–$2.00/$2.00–$2.50/more than $2.50/other)	(13/42/29/12/4/1)
When you are searching for a shared e-scooter, how long are you	(0−2 Minutes/3−5 Minutes/6−8 Minutes/Up to 10	(36/46/9/5/4)

willing to walk/travel to find an available e-scooter?	Minutes/Up to 15 Minutes)	
If you were offered a $1 discount on your next e-scooter trip for leaving the e-scooter at a designated place, how long would you be willing to walk from that designated place to your final destination?	(0−2 Minutes/3−5 Minutes/6−8 Minutes/Up to 10 Minutes/Up to 15 Minutes)	(26/50/12/8/4)
When was your last e-scooter trip?	(Today/Yesterday/This week/Last week/This Month/Within the last 365 days)	(4/3/8/4/11/70)
Thinking about your last shared e-scooter trip, if a shared e-scooter was not available, how would you have made that trip?	(Walk/Personal bike/Bus/Metro rail/Uber, Lyft/ Taxi/Drive a personal vehicle, car share vehicle, or other motor cycle/Car sharing/Ride with, dropped off by a friend, family member, or other person/I would not have made this trip/Other)	(69/4/8/1/5/0/7/0/3/2/1)
For your most recent e-scooter trip, how did you get to the location where you picked up the e-scooter?	(Walk/Personal bike/Bus/Metro rail/Uber, Lyft/Taxi/Drive a personal vehicle, car share vehicle, or other motor cycle/Car sharing/Ride with, dropped off by a friend, family member, or other person/I would not have made this trip/Other)	(86/1/7/1/2/2/2/0/0)
What is one thing that you would like to change the most about e-scooter service?	(The number of available units in my area/Ease of finding a nearby unit/Price/Dedicated e-scooter lane/App improvement/Faster e-scooters/Other)	(22/19/32/15/4/4/4)
Do you have your own car?	(Yes/No)	(67/33)
How many miles on average do you drive daily?	(0–5 miles/5–10 miles/10–15 miles/15+ miles)	(34/37/16/13)
What is the highest level of education you have completed or are currently pursuing?	(High School, GED/Associate's/Bachelor's/Masters/Doctorate/ Other)	(10/4/55/19/10/2)
What age group best describes you?	(Under 18/18–25/26–35/36–45/46–60/61 and above)	(2/67/22/6/3/0)
What is your gender?	(Male/Female/Other)	(36/63/1)
What is your estimated annual income?	(I currently have no income/$1–$20,000/$20,001–$40,000/$40,001–$60,000/$40,001–$60,000/$60,001–$80,000/$80,001–$100,000/More than $100,000)	(30/33/20/10/3/2/3)
QB1.1–QB1.6		
Did you use a station-based or dock-less shared bike? (Dock-less: You can leave the bike almost anywhere once your ride is over. Station-based: You must return the	(Station-based/Dock-less/Both stationed and dock-less/Cannot remember)	(35/41/17/7)

bike to a designated station with docks before ending the ride.)		
Do you prefer any of the following more than other?	(Station-Based/Dock-less/No preference)	(20/49/31)
Why do you prefer dock-less bikes over station-based ones?	(Can leave them anywhere once I am done riding/Easier to get to, find/They are cheaper/Other)	(78/22/0/0)
Why do you prefer station based bikes over dock-less ones?	(Makes less mess in the city/Easy to find nearby docks/The bikes are better maintained/Other)	(27/42/26/5)
What is the average distance of your bike share trips?	(You can look up this information in your bike share app) (0–1 miles/1–5 miles/5–10 miles/10+ miles)	(21/69/10/0)
How often do you use bike share to access a bus/shuttle, Metro rail, or commuter rail?	(Never/1–2 times a year/1–2 times per quarter/1–2 times per month/3–5 times per month/5+ times per month/A few times a week/Almost every day)	(37/16/4/17/8/5/7/6)
What is the maximum price (in U.S Dollars) that you are willing to pay for a recurring 1-mile trip using shared bikes (above that price you will switch to other modes of transportation)?	(Less than $1.00/$1.00–$1.50/$1.51–$2.00/$2.01–$2.50/more than $2.50/Other)	(16/38/24/20/2/0)
When you are searching for a bike share, how long are you willing to travel to find an available bike?	(0–2 Minutes/3–5 Minutes/6–8 Minutes/Up to 10 Minutes/Up to 15 Minutes)	(19/53/18/10/0)
If you were offered a $1 discount on your next bike share trip for leaving the bike at a designated place, how long would you be willing to walk from that designated place to your final destination?	(0–2 Minutes/3–5 Minutes/6–8 Minutes/Up to 10 Minutes/Up to 15 Minutes)	(25/41/26/8/0)
When was your last shared bike trip?	(Today/Yesterday/This week/Last week/This month/This year)	(2/3/11/15/18/51)
If bike-sharing were not available for your last trip, how would you have made that trip?	Walk/Personal bike/Bus/Metro rail/Uber, Lyft/Taxi/Drive a personal vehicle, car share vehicle, or other motor cycle/Car sharing/Ride with, dropped off by a friend, family member, or other person/I would not have made this trip/Other)	(48/8/17/0/7/2/11/3/3/1/0)
Still thinking of your most recent bike share trip, how did you get to the location where you picked up the bike?	(Walk/Public transportation/Drive a personal vehicle, car share vehicle, or other motor cycle/Taxi/Uber, Lyft/Ride with, dropped off by a friend, family member, or other person/Other)	(78/7/12/1/1/1/0)
In the past month, how many times did you use a bike share service to make a trip that you would not	(0 times/1–2 times/3–5 times/6–10 times/11 or more times)	(44/31/16/5/4)

have made otherwise if such services were not available?		
Please estimate how using a shared bike service changed your average WEEKLY travel costs, compared to what you were spending before these services were available?	(Spending >$20 more each week/Spending $10 to $20 more each week/Spending $1 to $10 more each week/No change/Saving $1–$20 per week/Saving $21–$40 per week/Saving $41–$60 per week/Saving more than $60 per week/Not sure)	(5/9/26/21/23/1/1/0/14)
What is one thing that you would like to change about bike share service?	(The number of available units in your area/Ease of finding a nearby unit/Price/App improvements/Not having to worry about leaving the bike in a designated place/Other)	(22/31/24/9/12/2)
Do you have your own car?	(Yes/No)	(56/44)
How many miles do you drive daily on average?	(0–5 miles/5–10 miles/10–15 miles/15+ miles)	(39/31/16/14)
Would you consider using a bike rental for short trips (less than 0.5 miles)?	(Yes/No)	(82/18)
What is your highest degree level (or the one that you are currently pursuing)?	(High School, GED/Associate's/Bachelor's/Masters/Doctorate/ Other)	(0/8/51/23/17/1)
What is your age?	(Under 18/18–25/26–35/36–45/46–60/61 and above)	(0/55/33/10/2/0)
What is your gender?	(Male/Female/Other)	(41/58/1)
What is your estimated annual income?	(I currently have no income/$1–$20,000/$20,001–$40,000/$40,001–$60,000/$40,001–$60,000/$60,001–$80,000/$80,001–$100,000/More than $100,000)	(19/28/23/11/13/3/3)

APPENDIX B. INDIANAPOLIS SURVEY

Following are additional figures and tables that were discussed in the analysis section.

Table B.1 Summary of reviewed articles using choice experiments

Authors	Study Year	Study Area	Target Population	Sampling Strategy	Distribution Method	Number of Resp.	Modes In Choice Experiment	Firs/Last Mile	Attributes	Model Used	Objective	Choice Per Resp.	General Topic
(Gkartzonikas & Gkritza, 2019)	2019	Review											Acceptability and opinion on AVs
(Jin et al., 2020)	2018	Beijing, China	General population	Convenience sample	Paper questionnaire	512	Public transport, taxi, private vehicle, and battery electric vehicle sharing	Yes (For BEV)	Access and egress distances, remaining range, vehicle mode, discount	Nested logit model	Examines the mode choice mechanism when battery electric vehicles sharing is part of the system	18	Commuter mode choice behavior
(Li et al., 2020)	2009	Sydney, Australia	General population	Not mentioned	Previous study	524	Car, city rail, proposed metro	Yes	Cost, time, number of transfers, crowding for public transportation	Mixed multinomial logit	Compares the values of time saving of both SP and RP and check the difference	6	Commuter mode choice behavior
(Ho et al., 2020)	2018	Tyneside, UK	General population	Stratified random sampling	Computer-Assisted Personal Interview	290	Car-sharing, bike-sharing, public transportation, taxi	No	Hour of use in the bundle, days with unlimited use, monthly hours of use of carshare, car-sharing scheme, advance booking time, hourly rate if PayG, % discount off every taxi bill, Rate of 30 minutes rent if PayG, daily fare, credit, price tag	Non-linear model (Ho et al., 2018). Can be re-written as MNL	Investigates the demand for different subscription options depending on different preferences and willingness to pay levels for mobility services	4	Preferences for transformative transportation services
(Liu et al., 2019)	2017	New York City, U.S.	General population	Not mentioned	Online	1,507	Uber (without ride-hailing), UberPool (with ridesharing, current travel mode of the respondent	No	Walking and waiting time, in-vehicle travel time, trip cost per mile, parking cost, powertrain, and automation	Multinomial logit model (MNL)	Develops a framework that integrates mode choice models with system for modeling real time on demand mobility services with varying interaction with other competing travel modes, varying passenger capacities, along with optimizing the supply side parameters (fleet size, fare)	6	Preferences for transformative transportation services
(Wu et al., 2019)	2018	London, UK	Users of the DriveNow FFCS service in London	Convenience sample	Online	289	Game 1 and 2: FFCS vehicles A & B, car, app-based taxi, bus. Game 3: Reserve FFCS in	No	Game 1 and 2: Waiting time, walking time, driving/riding time, price. Game 3:	Multinomial logit model (MNL)	Examines users' preferences regarding new reservation options for carsharing: virtual queuing and guaranteed		Preferences for transformative transportation services

							advance, or wait and use on demand		Walking time, Price		advance reservation. These new options address imbalances between supply and demand of FFCS. This is achieved using 3 choice experiments or games		
(Yan et al., 2019)	2017	University of Michigan	University of Michigan faculty, staff, and students	Convenience sample	Online	1,353	Car, integrated transit, bike, and walking	No	In-vehicle time, walking time, waiting time, parking time, transfers, and additional pickups	RP MNL model, an SP mixed logit model, and an RP-SP mixed logit model	Explores travelers' response to a proposed on campus integrated bus system called "Mtransit" consisting of: fixed bus routes and on demand shuttles serving as first/last mile feeder solution	9	Preferences for transformative transportation services
(Arentze & Molin, 2013)	2011–2012	The Netherlands	General population	Stratified random sampling	Online	2,746	Experiment 1: Bicycle, car, public transportation (PT). Experiment 2: Car, PT, Car + PT. Experiment 3: Bus, local train, Intercity train. Experiment 4: Train with access/egress modes: Walk, bicycle, and bus/tram/metro	Yes	For the different experiments: Access time–walking, wait for PT, main travel time, parking search time, walk to destination, possible delay, travel costs, parking costs, car detour travel, transfer time, next PT travel time, access time, egress time, facilities at station, seat availability, wait for PT egress, travel costs access/egress/main	Scaled error-component-mixed multinomial logit framework	Using four experiments, they examine how attributes change with the distance of trips and attributes. They also examine how multimodality plays a role for a certain distance	9	Opinion on first/last mile trips
(Yap et al., 2016)	NA	The Netherlands	General population	Interlocked stratified sample	Online	761	Car, Train plus egress modes: Bus/tram/metro, bicycle, cybercar (AV) drive yourself, cybercar shared	Yes	Travel time, waiting time, walking time, travel costs, parking costs, sharing AV	Standard multinomial logit models	Explore the preferences for AVs in the transportation market as a last mile mode	6	Opinion on first/last mile trips
(McQueen, 2020)	2020	Portland, U.S.	Portland State University students	Convenience sample	Online	1,968	Car, bicycle, and e-scooter + MAX	Yes	In-vehicle time, walking time, parking cost, mode cost	Multinomial logit model (MNL)	Understand the relationship of travel time and cost in addition to other covariates on mode choice (car, bike, and e-scooter + MAX choices) for students' commute	6	Opinion on first/last mile trips

(Arendsen, 2019)	2019	The Netherlands	NS (Dutch rail company) customer database	Semi-random sample based on address	Online	1,835	walking, private bike, shared bike, bus/tram/metro, private car, shared e-scooter, shared car	Yes	Search time, parking time, in-vehicle time, usage costs, unlock method, waiting time, ticket cost, parking cost	Multinomial logit model (MNL)	Explore the users' willingness to use transformative transportation modes for multimodal train trips	6

Table B.2 Weighting of the survey observations according to age, gender, and income

Age	Gender	Income	Census Total	Census %	Survey Total	Survey %	Weights
18–24	Female	Less than 50k	22,377	3.3%	21	5.3%	0.62
		Between 50k and 100k	11,044	1.6%	6	1.5%	1.06
		More than 100k	8,233	1.2%	1	0.3%	4.76
18–24	Male	Less than 50k	17,522	2.5%	4	1.0%	2.53
		Between 50k and 100k	12,717	1.8%	3	0.8%	2.45
		More than 100k	10,064	1.5%	1	0.3%	5.82
25–34	Female	Less than 50k	35,316	5.1%	26	6.5%	0.79
		Between 50k and 100k	27,800	4.0%	5	1.3%	3.21
		More than 100k	16,386	2.4%	12	3.0%	0.79
25–34	Male	Less than 50k	28,289	4.1%	16	4.0%	1.02
		Between 50k and 100k	28,217	4.1%	4	1.0%	4.08
		More than 100k	17,911	2.6%	10	2.5%	1.04
35–44	Female	Less than 50k	24,330	3.5%	31	7.8%	0.45
		Between 50k and 100k	21,073	3.1%	13	3.3%	0.94
		More than 100k	15,305	2.2%	22	5.5%	0.40
35–44	Male	Less than 50k	21,019	3.1%	16	4.0%	0.76
		Between 50k and 100k	21,633	3.1%	14	3.5%	0.89
		More than 100k	15,489	2.3%	14	3.5%	0.64
45–54	Female	Less than 50k	21,650	3.1%	18	4.5%	0.70
		Between 50k and 100k	19,177	2.8%	12	3.0%	0.92
		More than 100k	16,824	2.4%	5	1.3%	1.95
45–54	Male	Less than 50k	18,148	2.6%	6	1.5%	1.75
		Between 50k and 100k	17,945	2.6%	3	0.8%	3.46
		More than 100k	16,813	2.4%	3	0.8%	3.24
55–64	Female	Less than 50k	24,929	3.6%	16	4.0%	0.90
		Between 50k and 100k	18,815	2.7%	10	2.5%	1.09
		More than 100k	15,218	2.2%	11	2.8%	0.80
55–64	Male	Less than 50k	19,146	2.8%	6	1.5%	1.84
		Between 50k and 100k	16,831	2.4%	6	1.5%	1.62
		More than 100k	16,139	2.3%	3	0.8%	3.11
65 and over	Female	Less than 50k	37,851	5.5%	26	6.5%	0.84
		Between 50k and 100k	17,157	2.5%	17	4.3%	0.58
		More than 100k	96,96	1.4%	5	1.3%	1.12
65 and over	Male	Less than 50k	22,180	3.2%	12	3.0%	1.07
		Between 50k and 100k	15,261	2.2%	14	3.5%	0.63
		More than 100k	9,886	1.4%	6	1.5%	0.95
Total			688,391				

Table B.3 Summary table of the Indianapolis survey: mode overview questions

Variable	**Description**	**Response Frequency (%)**
Walk—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	10/24/12/36/18
Car—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	5/21/1/71/2
Taxi—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	8/3/13/1/74
Transit—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	9/5/12/3/71
Bike-sharing—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	4/5/7/1/83
E scooter sharing—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	5/3/6/0/85
Ride-hailing—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	13/7/33/1/46
Personal bike—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	13/12/15/5/55
Personal e-scooter—Before pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	2/3/3/1/90
Walk—Post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	12/30/9/31/18
Car—Post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	9/33/1/54/3
Taxi—Post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	4/3/10/0/82
Transit—Post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	5/4/8/2/81
Bike-sharing—Post-pandemic	A few times a month/A few	3/2/5/0/89

	times a week/A few times a year/Daily/Never	
E scooter sharing—Post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	3/3/4/0/90
Ride-hailing—Post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	9/7/24/1/58
Personal bike—Post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	10/11/10/5/64
Personal e scooter—Post pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	3/3/2/1/91

Table B.4 Summary table of the Indianapolis survey: mode choice if bus is not available questions

Variable	**Description**	**Response Frequency (%)**
Work—bus not available	Bike-sharing/Car/I would not have made this trip/Personal bike/Ride-hailing/Scooter-sharing/Taxi/Walk	2/55/18/1/9/0/4/11
Shopping—bus not available	Bike-sharing/Car/I would not have made this trip/Personal bike/Ride-hailing/Scooter-sharing/Taxi/Walk	1/68/7/1/0/9/1/4/9
Personal—bus not available	Bike-sharing/Car/I would not have made this trip/Personal bike/Ride-hailing/Scooter-sharing/Taxi/Walk	2/60/17/3/8/1/3/7
Social—bus not available	Bike-sharing/Car/I would not have made this trip/Personal bike/Ride-hailing/Scooter-sharing/Taxi/Walk	1/56/20/2/1/7/1/3/9

Table B.5 Summary table of the Indianapolis survey: trip purpose questions

Variable	**Description**	**Response Frequency (%)**
Work—pre-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	3/15/3/56/24
Shopping—pre-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	18/63/2/15/2
Personal—pre-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	33/43/12/6/7
Social—pre-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	35/40/9/12/4
Work—post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	8/19/3/36/34
Shopping—post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	40/46/3/7/5
Personal—post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	37/25/20/3/16
Social—post-pandemic	A few times a month/A few times a week/A few times a year/Daily/Never	42/24/18/3/13

Table B.6 Summary table of the Indianapolis survey: work trip attributes

Variable	**Description**	**Response Frequency (%)**
COST: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	19/23/16/19/23
TRAVEL TIME: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	17/28/8/15/32
WAITING TIME: Work trip,	Extremely	18/31/7/15/29

Before pandemic	important/Moderately important/Not at all important/Slightly important/Very important	
RELAIBILITY: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	37/11/1/7/44
CONVENIENCE AND ACCESSIBILITY: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	26/21/2/43/8
COMFORT: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important Very important	19/33/2/10/36
SAFETY: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	49/15/2/3/32
ENVIRONMENT: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	25/28/5/11/30
HEALTH: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	36/18/3/7/37
TRAVEL COMPANIONS: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	17/22/22/15/24
SOCIAL IMAGE: Work trip, Before pandemic	Extremely important/Moderately important/Not at all important/Slightly	10/21/37/18/13

	important/Very important	
COST: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	24/26/11/14/24
TRAVEL TIME: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	23/30/5/14/28
WAITING TIME: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	22/29/5/11/32
RELIABILITY: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	44/15/2/4/35
CONVENEINCE AND ACCESSIBILITY: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	30/24/3/5/38
COMFORT: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	27/30/4/11/29
SAFETY: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	53/11/2/2/32
HEALTH: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	50/12/2/4/32
ENVIRONMENT: Work trip, Post pandemic	Extremely important/Moderately	33/25/5/9/28

	important/Not at all important/Slightly important/Very important	
TRAVEL COMPANIONS: Work trip, Post pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	23/21/21/14/20
SOCIAL IMAGE: Work trip, Post Pandemic	Extremely important/Moderately important/Not at all important/Slightly important/Very important	12/20/39/15/14

Table B.7 Summary table of the Indianapolis survey: transformative transportation technology

Variable	**Description**	**Response Frequency (%)**
Have you ever used that bike-sharing service?	No/Yes	84/16
Have you ever used one of these shared e-scooter services?	No/Yes	82/18
Have you ever used the ride-hailing services?	No/Yes	38/62
Have you reduced the number of automobiles you (or your family) own as a result of being able to use bike-sharing, shared e-scooter, OR ride-hailing?	No/No, but I have considered it/Yes	79/13/9
When was the last time you used this shared e-scooter service?	A few days ago/A few weeks ago/Last week/More than a month ago	16/7/30/47
Are you a member of any shared e-scooter service?	No/Yes	53/48
Prior to the pandemic, did you consider shared e-scooter to be your primary mode for certain trip purposes/destinations?	No/Yes	69/31
Now that the pandemic has come about, do you consider shared e-scooter to be your	No/Yes	66/34

primary mode for certain trip purposes/destinations?		
For which trip purpose do/did you use shared e-scooter as a primary mode?	None//Personal (Church, medical, or family business)//Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)//Shopping (Running errands)//Shopping (Running errands), Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)/Social (recreational, visit friends/relatives)//Work (Or school for students and work-Related Business)//Work (Or school for students and work-Related Business),Shopping (Running errands)//Work (Or school for students and work-related business),Shopping (Running errands), Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)//Work (Or school for students and work-Related Business), Social (Recreational, visit friends/relatives)	3/11/8/24/3/16/24/3/5/5
Which mode did shared e-scooter replace as the primary mode? **Work trip**	Car/Ride-hailing (Uber, Lyft)/Walk	78/7/15
Which mode did shared e-scooter replace as the primary mode? **Shopping trip**	Bike-sharing (Indiana Pacers)/Car/Personal bike/Personal e-scooter/Taxis (Yellow Cab)/Transit/Walk	5/40/7/9/7/15/17
Which mode did shared e-scooter replace as the primary mode? **Personal trip**	Car/Personal bike/Ride-hailing (Uber, Lyft)/Transit/Walk	22/9/45/6/18
Which mode did shared e-scooter replace as the primary mode? **Social trip**	Bike-sharing (Indiana Pacers)/Car/Personal bike/Personal e-scooter/Ride-hailing (Uber, Lyft)/Walk	7/59/6/7/4/18
Since you started using shared e-scooter do you find you use the following options more or less? **Walk**	About the same/Less often/More often	61/28/11
Since you started using shared e-scooter do you find you use the following options more or less? **Car**	About the same/Less often/More often	56/18/26
Since you started using shared e-scooter do you find you use	About the same/Less often/More often	32/64/3

the following options more or less? **Taxis (Yellow Cab)**		
Since you started using shared e-scooter do you find you use the following options more or less? **Transit (Bus)**	About the same/Less often/More often	30/64/6
Since you started using shared e-scooter do you find you use the following options more or less? **Ride-hailing**	About the same/Less often/More often	41/43/15
Since you started using shared e-scooter do you find you use the following options more or less? **Bike-sharing**	About the same/Less often/More often	43/45/12
Since you started using shared e-scooter do you find you use the following options more or less? **Personal bike**	About the same/Less often/More often	60/32/8
Since you started using shared e-scooter do you find you use the following options more or less? **Personal scooter**	About the same/Less often/More often	37/51/11
If shared e-scooter had not been available for your last trip, which mode would you have used? (Select only one.)	Bike-sharing (Indiana Pacers)/Car/Personal bike/Personal e-scooter/Ride-hailing (Uber, Lyft)/Taxi (Yellow Cab)/Transit (IndyGo bus)/Walk/Would not have made this trip	3/32/9/1/16/2/3/34/1
Have you ever had an accident involving shared e-scooter?	No/Yes	84/16
I feel safe from contracting COVID-19 when I am using shared e-scooter.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	31/25/7/26/12
When was the last time you used this bike-sharing service?	A few days ago/A few weeks ago/Last week/More than a month ago	19/6/33/43
Are you a member of any bike-sharing service?	No/Yes	53/47
Prior to the pandemic, did you consider bike-sharing to be your primary mode for certain trip purposes/destinations?	No/Yes	57/43
Now that the pandemic has come about, do you consider bike-sharing to be your primary	No/Yes	60/40

mode for certain trip purposes/destinations?		
For which trip purpose do/did you use bike-sharing as a primary mode?	None//Personal (Church, medical, or family business)//Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)//Shopping (Running errands)//Shopping (Running errands), Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)/Social (Recreational, visit friends/relatives)//Work (Or school for students and work-Related Business)//Work (Or school for students and work-Related Business), Shopping (Running errands)//Work (Or school for students and work-Related Business), Shopping (Running errands), Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)//Work (Or school for students and work-Related Business), Social (Recreational, visit friends/relatives)	3/5/27/12/1/2/7/21/1/12/4/4/2
Which mode did bike-sharing replace as the primary mode? **Work trip**	Car/Shared e-scooter (Bird, Lime, etc.)/Transit/Walk	84/4/4/9
Which mode did bike-sharing replace as the primary mode? **Shopping trip**	Car/Personal bike/Personal e-scooter/Ride-hailing (Uber, Lyft)/Taxis (Yellow Cab)/Transit/Walk	31/10/3/21/3/4/28
Which mode did bike-sharing replace as the primary mode? **Personal trip**	Car/Personal bike/Personal e-scooter/Ride-hailing (Uber, Lyft)/Walk	20/4/8/37/32
Which mode did bike-sharing replace as the primary mode? **Social trip**	Car/Personal e-scooter/Ride-hailing (Uber, Lyft)/Taxis (Yellow Cab)/Walk	47/7/13/10/23
Since you started using bike-sharing do you find you use the following options more or less? **Walk**	About the same/Less often/More often	52/22/25
Since you started using bike-sharing do you find you use the following options more or less? **Car**	About the same/Less often/More often	53/17/30
Since you started using bike-sharing do you find you use the	About the same/Less often/More often	39/59/3

following options more or less? **Taxis (Yellow Cab)**		
Since you started using bike-sharing do you find you use the following options more or less? **IndyGo Bus**	About the same/Less often/More often	36/58/6
Since you started using bike-sharing do you find you use the following options more or less? **Ride-hailing Uber**	About the same/Less often/More often	39/44/17
Since you started using bike-sharing do you find you use the following options more or less? **Shared e-scooter**	About the same/Less often/More often	31/54/15
Since you started using bike-sharing do you find you use the following options more or less? **Personal bike**	About the same/Less often/More often	59/27/14
Since you started using bike-sharing do you find you use the following options more or less? **Personal scooter**	About the same/Less often/More often	41/52/7
If bike-sharing had not been available for your last trip, which mode would you have used? (Select only one.)	Car/Shared e-scooter (Bird, Lime, etc.)/Personal bike/Ride-hailing (Uber, Lyft)/Taxi (Yellow Cab)/Walk/Would not have made this trip	46/6/3/11/4/28/1
Have you ever had an accident involving bike-sharing?	No/Yes	85/15
I feel safe from contracting COVID-19 when I am using bike-sharing.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	18/48/10/23/1
When was the last time you used this ride-hailing service?	A few days ago/A few weeks ago/Last week/More than a month ago	9/19/9/64
Are you a member of any ride-hailing service?	No/Yes	70/30
Prior to the pandemic, did you consider ride-hailing to be your primary mode for certain trip purposes/destinations?	No/Yes	68/32
Now that the pandemic	No/Yes	84/16

has come about, do you consider ride-hailing to be your primary mode for certain trip purposes/destinations?		
For which trip purpose do/did you use ride-hailing as a primary mode?	None//Personal (Church, medical, or family business)//Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)//Shopping (Running errands)//Shopping (Running errands), Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)/Social (Recreational, visit friends/relatives)//Work (Or school for students and work-Related Business)//Work (Or school for students and work-Related Business),Shopping (Running errands)//Work (Or school for students and work-Related Business), Shopping (Running errands), Personal (Church, medical, or family business), Social (Recreational, visit friends/relatives)//Work (Or school for students and work-Related Business), Social (Recreational, visit friends/relatives)	2/9/4/18/3/1/2/23/24 /2/2/5/1/2/1/2
Which mode did bike-sharing replace as the primary mode? **Work trip**	Car/Shared e-scooter (Bird, Lime, etc.)/Taxis (Yellow Cab)/Transit/Walk	26/1/2/3/3
Which mode did bike-sharing replace as the primary mode? **Shopping trip**	Bike-sharing (Indiana Pacers)/Car/Taxis (Yellow Cab)/Transit/Walk	1/51/16/11/21
Which mode did bike-sharing replace as the primary mode? **Personal trip**	Car/Personal bike/Taxis (Yellow Cab)/Transit)/Walk	51/4/14/11/20
Which mode did bike-sharing replace as the primary mode? **Social trip**	Car/Personal bike/Taxis (Yellow Cab)/Transit/Walk	74/5/10/4/9
Since you started using	About the same/Less often/More often	62/22/16

bike-sharing do you find you use the following options more or less? **Walk**		
Since you started using bike-sharing do you find you use the following options more or less? **Car**	About the same/Less often/More often	60/23/18
Since you started using bike-sharing do you find you use the following options more or less? **Taxis (Yellow Cab)**	About the same/Less often/More often	37/60/3
Since you started using bike-sharing do you find you use the following options more or less? **Transit (IndyGo Bus)**	About the same/Less often/More often	44/53/3
Since you started using bike-sharing do you find you use the following options more or less? **Bike-sharing**	About the same/Less often/More often	44/54/2
Since you started using bike-sharing do you find you use the following options more or less? **Shared e-scooter**	About the same/Less often/More often	46/50/5
Since you started using bike-sharing do you find you use the following options more or less? **Personal bike**	About the same/Less often/More often	58/36/6
Since you started using bike-sharing do you find you use the following options more or less? **Personal e-scooter**	About the same/Less often/More often	48/48/5
If bike-sharing had not been available for your last trip, which mode would you have used? (Select only one.)	Bike-sharing (Indiana Pacers)/Car/Shared e-scooter (Bird, Lime, etc.)/Personal bike/Personal e-scooter/Taxi (Yellow Cab)/Transit (IndyGo bus)/Walk/Would not have made this trip	2/61/3/1/0/12/5/9/6

Have you ever had an accident involving bike-sharing?	No/Yes	95/5
I feel safe from contracting COVID-19 when I am using bike-sharing.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	35/26/15/16/8
I use ride-hailing service to: Go to the airport	Always/Never/Often/Rarely/Sometimes	6/32/18/18/27
I use ride-hailing service to: Use phone or PC while on the road	Always/Never/Often/Rarely/Sometimes	9/43/12/12/23
I use ride-hailing service to: Avoid drunk-driving	Always/Never/Often/Rarely/Sometimes	41/27/11/10/11

Table B.8 Summary table of the Indianapolis survey: multimodality

Variable	**Description**	**Response Frequency (%)**
Generally, do you make mode transfers* (Or change mode) to complete your trips?	No/Yes	80/20
Which modes do you use for each destination/purpose? **Work (Or school for students and work-related business)**	Bus/Bus, Bike-sharing/Bus, Personal bike/Bus, Ride-hailing/Car/Car, Bike-sharing/Car, Bus/Car, Personal bike/Car, Ride-hailing/Car, Ride-hailing, Personal e-scooter/Car, Taxi/e-scooter-sharing/Personal bike/Ride-hailing/Taxi, Bike-sharing, e-scooter-sharing/Walk/Walk, Bus/Walk, Bus, Personal bike/Walk, Car/Walk, Car, Bike-sharing, Personal bike/Walk, Car, Bus/Walk, Car, Personal bike/Walk, Car, Taxi/Walk, Personal bike/Walk, Ride-hailing/Walk, Ride-hailing, Bike-sharing	1/5/2/1/18/0/4/1/5/1/2/1/0/2/1/13/12/0/20/1/4/1/0/1/2/1
Which modes do you use for each destination/purpose? **Shopping (Running errands)**	Bike-sharing/Bike-sharing, Personal bike, Personal e-scooter/Bus/Bus, Personal bike/Bus, Ride-hailing/Car/Car, Bus/Car, Bus ,/Car, e-scooter-sharing/Car, Personal bike/Car, Ride-hailing/e-scooter-sharing/Ride-hailing/Taxi/Taxi, Personal bike/Walk/Walk, Bus/Walk, Car/Walk, Car, Bus/Walk, Car, Personal bike/Walk, Car, Taxi/Walk, Personal bike/Walk, Ride-hailing/Walk, Ride-	3/0/3/1/2/44/3/1/1/2/4/3/1/0/1/10/8/1/1/1/3/1/1/0/1

	hailing, Bike-sharing/Walk, Taxi/Walk, Taxi, Bus	
Which modes do you use for each destination/purpose? **Family (Church, medical, or family business)**	Bike-sharing/Bike-sharing, e-scooter-sharing, Personal bike/Bus/Bus, e-scooter-sharing/Bus, E scooter-sharing, Personal e-scooter/Car/Car, Bus/Car, e-scooter-sharing/Car, Personal bike/Car, Ride-hailing/Car, Ride-hailing, Bike-sharing/Car, Taxi, Bus/e-scooter-sharing/Personal bike/Personal e-scooter/Ride-hailing/Ride-hailing, Personal bike/Taxi/Taxi, Bus/Walk/Walk, Bike-sharing/Walk, Bus/Walk, Car/Walk, Car, Bus/Walk, Car, Personal bike/Walk, Car, Ride-hailing/Walk, Car, Taxi/Walk, Car, Taxi, Bus/Walk, Personal bike/Walk, Ride-hailing/Walk, Taxi, Ride-hailing, Bike-sharing	0/0/2/1/0/33/3/1/1/6/0/1/2/5/0/5/0/1/1/6/1/6/8/3/1/1/1/1/2/3/1
Which modes do you use for each destination/purpose? **Social (Recreational, visit friends/relatives)**	Bike-sharing/Bike-sharing, e-scooter-sharing/Bus/Bus, e-scooter-sharing/Bus, Ride-hailing/Car/Car, Bike-sharing/Car, e-scooter-sharing/Car, Ride-hailing/Car, Taxi, Bike-sharing/Car, Taxi, Ride-hailing/e-scooter-sharing/Personal bike/Personal e-scooter/Ride-hailing/Ride-hailing, Bike-sharing/Taxi, Bike-sharing/Taxi, e-scooter-sharing/Walk/Walk, Bus/Walk, Car/Walk, Car, Bus/Walk, Car, Bus, Personal bike/Walk, Car, Personal bike/Walk, Car, Ride-hailing/Walk, Car, Ride-hailing, Bike-sharing/Walk, Car, Taxi/Walk, Personal bike/Walk, Ride-hailing/Walk, Taxi	2/1/3/1/28/0/1/3/1/1/2/2/5/4/0/0/1/5/9/14/2/1/1/1/1/1/6/1/0
Prior to the pandemic, which mode was most used for your first/last mile trips*?	Bike-sharing (Indiana Pacers)/Bus (IndyGo)/Car/Shared e-scooter (Bird, Lime, etc.)/Personal bike/Ride-hailing (Uber, Lyft)/Walk	0/3/74/1/1/2/18
Prior to the pandemic, how often did you use these modes to access a bus? Shared e-scooter (Bird, Lime, etc.)	A few times a month/A few times a week/A few times a year/Daily/Never	5/7/5/2/81
Prior to the pandemic, how often did you use these modes to access a bus? Bike-sharing (Indiana Pacers)	A few times a month/A few times a week/A few times a year/Daily/Never	4/8/4/1/83
Now that the	A few times a month/A few times a week/A few	5/6/4/2/82

pandemic has come about, how often do you use these modes to access a bus? Shared e-scooter (Bird, Lime, etc.)	times a year/Daily/Never	
Now that the pandemic has come about, how often do you use these modes to access a bus? Bike-sharing (Indiana Pacers)	A few times a month/A few times a week/A few times a year/Daily/Never	4/5/6/3/83
Now that the pandemic has come about, how often do you use these modes to access a bus? Bike-sharing (Indiana Pacers)	A few times a month/A few times a week/A few times a year/Daily/Never	0/1/71/1/1/2/24

Table B.9 Summary table of the Indianapolis survey: preferences

Variable	**Description**	**Response Frequency (%)**
Bike-sharing or shared e-scooter services grant me more freedom to travel around downtown.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	32/34/7/16/12
Transformative transportation technology (Ride-hailing, bike-sharing or shared e-scooter) services make using the bus easier.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	46/21/10/10/13
Transformative transportation technology (Ride-hailing, bike-sharing or shared e-scooter) services solve the issue of finding a parking spot.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	20/38/7/26/9
Bike-sharing or shared e-scooter services grant me more freedom to travel in poor weather.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	26/12/19/5/38
I would start using any of the aforementioned transformative transportation services (Ride-hailing, bike-sharing or shared e-scooter) to avoid congestion.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	23/29/17/14/16

I would start using any of the aforementioned transformative transportation services (Ride-hailing, bike-sharing or shared e-scooter) if they cost less than the modes I have previously used.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	29/31/13/15/14
I would start using either bike-sharing or shared e-scooter if there were designated bike lanes.	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	29/25/12/17/17
Technology (Having to deal with a phone application) discourages me from using the transformative transportation services (Ride-hailing, bike-sharing or shared e-scooter).	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	28/25/14/13/20
Having to ride an e-scooter on the sidewalk discourages me from using the service (Ride-hailing, bike-sharing or shared e-scooter).	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	33/25/12/15/14
The absence of a basket (or a saddlebag) on an e-scooter discourages me from using the service (Especially for specific trip purposes such as shopping).	Neither agree nor disagree/Somewhat agree/Somewhat disagree/Strongly agree/Strongly disagree	33/31/9/15/12
How do you rate the probability of contracting COVID-19 from the use of the transportation modes listed below? Transit (IndyGo bus)	Average/High/Low/Very high/Very low	38/28/5/18/12
How do you rate the probability of contracting COVID-19 from the use of the transportation modes listed below? Taxis (Yellow cab)	Average/High/Low/Very high/Very low	37/22/16/13/12
How do you rate the probability of contracting COVID-19 from the use of the transportation modes listed below? Bike-sharing (Indiana Pacers)	Average/High/Low/Very high/Very low	27/15/24/6/28
How do you rate the probability of contracting COVID-19 from the use of the transportation modes listed below? Shared e-scooter	Average/High/Low/Very high/Very low	28/14/24/7/28
How do you rate the probability of contracting COVID-19 from the use of the transportation modes listed below? Ride-hailing (Uber, Lyft)	Average/High/Low/Very high/Very low	43/23/13/11/10

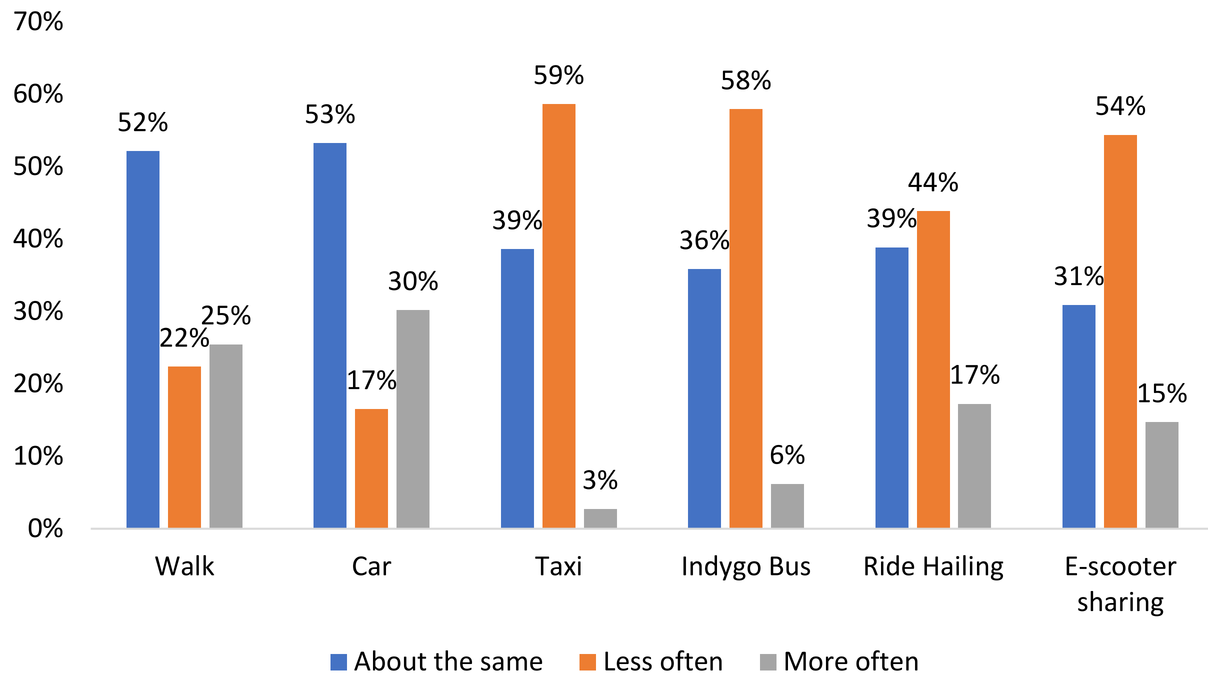


Figure B.1 Usage of other modes after starting to use bike-sharing.

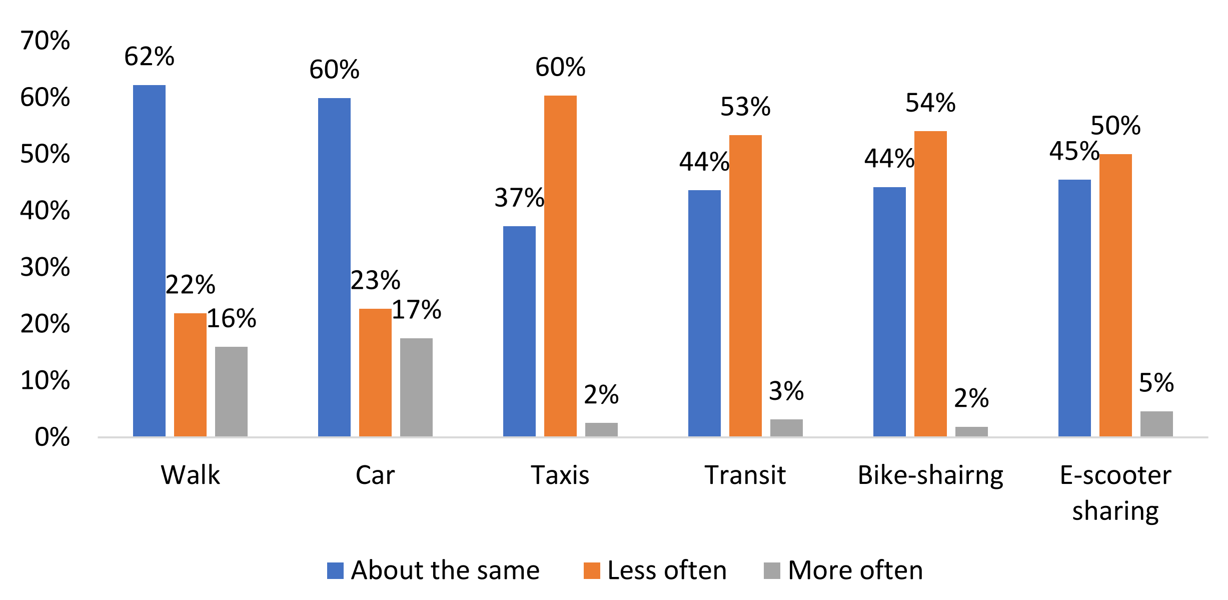


Figure B.2 Usage of other modes after starting to use ride-hailing.

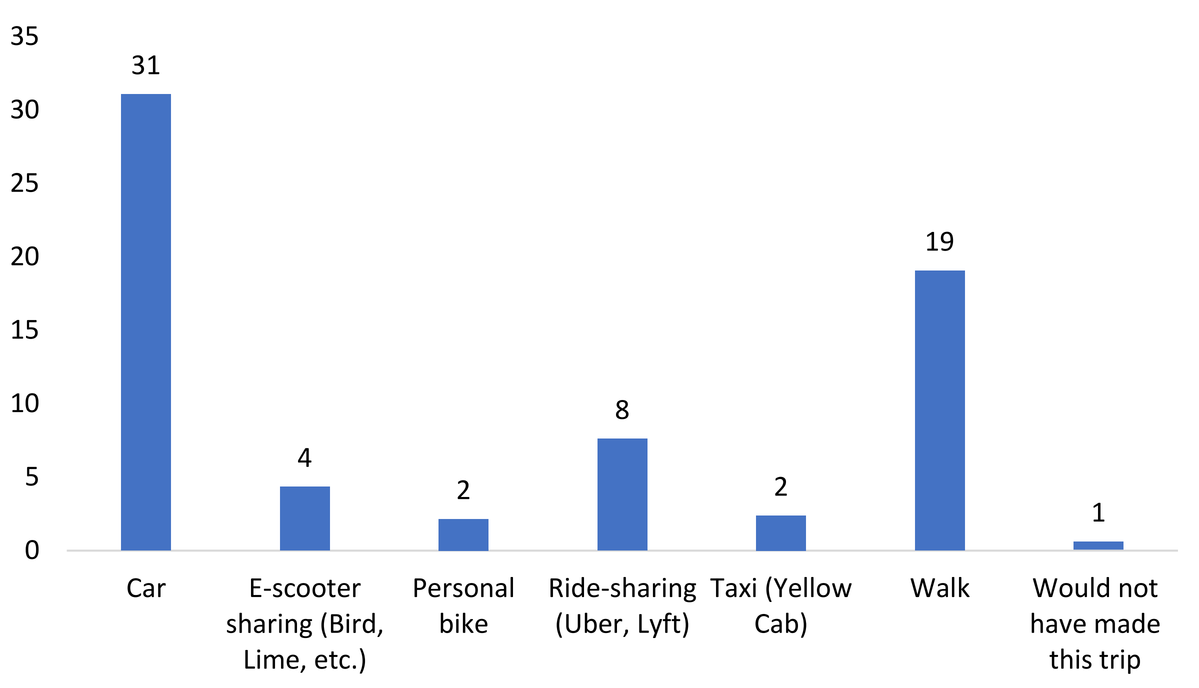


Figure B.3 Usage of other modes in case bike-sharing was not available for the last trip.

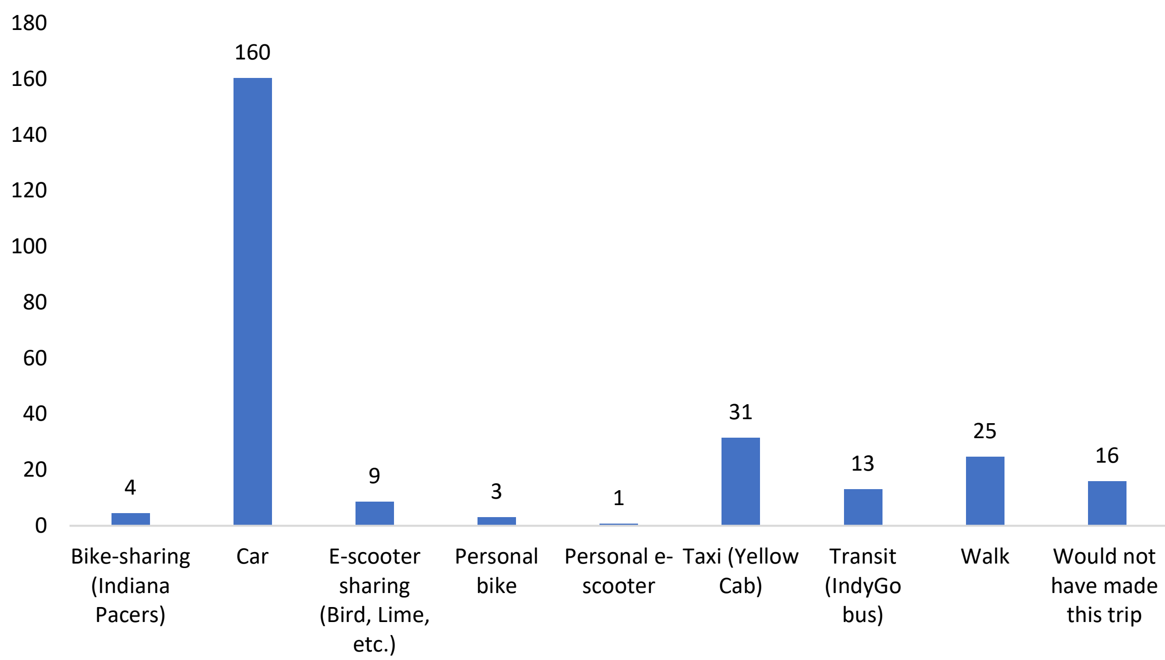


Figure B.4 Usage of other modes in case ride-hailing was not available for the last trip.

Table B.10 Travel mode marginal homogeneity test parameters

	Walk	Car	Taxi	Transit	Bike-sharing	e-scooters	Ride-hailing
Total N				424			
Test Statistic	257.000	286.000	131.000	113.000	87.000	70.000	173.000
Standard Error	12.258	11.435	10.210	10.932	8.588	7.566	12.679
Standardized Test Statistic	2.488	5.816	-3.771	-6.129	-2.620	-2.842	-6.428
Asymptotic Significance (2-sided test)	.013	<.001	<.001	<.001	.009	.004	<.001

Table B.11 Trip purpose marginal homogeneity test parameters

	Work	Shopping	Personal	Social
Total N		424		
Test Statistic	347.000	237.000	167.000	238.000
Standard Error	12.942	10.308	12.639	14.422
Standardized Test Statistic	1.545	5.772	-4.154	-2.011
Asymptotic Significance (2-sided test)	.122	<.001	<.001	.044

About the Joint Transportation Research Program (JTRP)

On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1—evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,600 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at http://docs.lib.purdue.edu/jtrp.

Further information about JTRP and its current research program is available at http://www.purdue.edu/jtrp.

About This Report

An open access version of this publication is available online. See the URL in the citation below.

Luo, H., Chahine, R., Rambaram, A., Rosenzweig, E. T., Gkritza, K., & Cai, H. (2022). *Assessing the travel demand and mobility impacts of transformative transportation technologies in Indiana* (Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2022/11). West Lafayette, IN: Purdue University. https://doi.org/10.5703/1288284317374