Final Project Report

Consumer Attitudes and Behavioral Implications in the New Era of Shared Mobility

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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August 2020

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. N/A	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A

4. Title and Subtitle
Consumer Attitudes and Behavioral Implications in the New Era of Shared Mobility

5. Report Date
August 2020

6. Performing Organization Code
N/A

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8. Performing Organization Report No.
N/A

9. Performing Organization Name and Address
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660 S. College Avenue, Tempe, AZ 85287-3005

10. Work Unit No. (TRAIS)
N/A

11. Contract or Grant No.
69A3551747116

12. Sponsoring Agency Name and Address
U.S. Department of Transportation,
University Transportation Centers Program,
1200 New Jersey Ave, SE, Washington, DC 20590

13. Type of Report and Period Covered
Research Report
(2019 – 2020)

14. Sponsoring Agency Code
USDOT OST-R

15. Supplementary Notes
N/A

16. Abstract
In the last few years, the concept of platform-based sharing economy has received tremendous attention (Sundararajan, 2016). This concept is mainly made possible by digital platforms that leverage advanced technologies (e.g., smartphones, GPS, integrated payment systems) to connect the demand and supply for a particular product or service in an efficient and cost effective manner. One such innovative use case is in the transportation industry where on-demand shared mobility—the real-time shared use of a vehicle, bicycle, or other transportation mode—is having transformative impacts on travelers' attitudes, mobility choices, and behavioral responses to a wide range of daily activities. The project originally aimed to (1) understand the perceptions, attitudes, and user's mobility choices toward dockless bike-sharing services, (2) develop advanced analytics and machine learning algorithms to uncover patterns associated with mobility choice, activity-travel, and additional spending related to dockless bike sharing, and (3) empirically evaluate if and how the introduction of the dockless bike-sharing services influences public transit ridership and business sales. COVID-19 in the early 2020 led to widespread lockdowns in many countries and significantly limited people's travel behaviors. Given the significant disruption of COVID-19 on travel and mobility, we slightly revised the research direction with the new research questions focused on (1) how COVID-19 influenced people's travel behaviors and patterns, especially dockless bike sharing and (2) how COVID-19 changed the perception and attitude of dockless bike sharing.

17. Key Words
Consumer Attitudes; Behavioral Implications; Shared Mobility

18. Distribution Statement
No restrictions.

19. Security Classif.(of this report) Unclassified	**20. Security Classif.(of this page)** Unclassified	**21. No. of Pages** 16	**22. Price** N/A

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

ACKNOWLEDGMENTS

This study was funded by a grant from A USDOT Tier 1 University Transportation Center, supported by USDOT through the University Transportation Centers program. The authors would like to thank the TOMNET and USDOT for their support of university-based research in transportation, and especially for the funding provided in support of this project.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

EXECUTIVE SUMMARY

In the last few years, the concept of platform-based sharing economy has received tremendous attention (Sundararajan, 2016). This concept is mainly made possible by digital platforms that leverage advanced technologies (e.g., smartphones, GPS, integrated payment systems) to connect the demand and supply for a particular product or service in an efficient and cost effective manner. One such innovative use case is in the transportation industry where on-demand shared mobility—the real-time shared use of a vehicle, bicycle, or other transportation mode—is having transformative impacts on travelers' attitudes, mobility choices, and behavioral responses to a wide range of daily activities. The project originally aimed to (1) understand the perceptions, attitudes, and user's mobility choices toward dockless bike-sharing services, (2) develop advanced analytics and machine learning algorithms to uncover patterns associated with mobility choice, activity-travel, and additional spending related to dockless bike sharing, and (3) empirically evaluate if and how the introduction of the dockless bike-sharing services influences public transit ridership and business sales. COVID-19 in the early 2020 led to widespread lockdowns in many countries and significantly limited people's travel behaviors. Given the significant disruption of COVID-19 on travel and mobility, we slightly revised the research direction with the new research questions focused on (1) how COVID-19 influenced people's travel behaviors and patterns, especially dockless bike sharing and (2) how COVID-19 changed the perception and attitude of dockless bike sharing.

INTRODUCTION

In the last few years, the concept of *platform-based sharing economy* has received tremendous attention (Sundararajan, 2016). This concept is mainly made possible by digital platforms that leverage advanced technologies (e.g., smartphones, GPS, integrated payment systems) to connect the demand and supply for a particular product or service in an efficient and cost effective manner. One such innovative use case is in the transportation industry where *on-demand shared mobility*—the real-time shared use of a vehicle, bicycle, or other transportation mode—is having transformative impacts on travelers' attitudes, mobility choices, and behavioral responses to a wide range of daily activities.

Among the shared mobility applications, *dockless bike-sharing services* suddenly became popular in 2017 (Qi et al., 2018).[1] Unlike traditional dock-based bike rent/share programs, dockless bike-sharing services do not require city funding or sponsorship for their infrastructure or operational management. Dockless bike share offers a flexible, low-cost, and alternative mode of transportation. A customer of the dockless bike share service uses a smart phone app to locate and unlock a bike nearby and rides it to the destination where he/she parks and locks the bike, making the bike available for other customers to use. While such a shared mobility application has a great potential to improve the efficiency of short-distance urban travel and create a positive impact on the community and environment (e.g., Alonso-Mora et al. 2017, Hall et al., 2017, Cramer and Krueger, 2016, Barbar and Burtch, 2017, Li et al., 2022), there is little research on the *attitudes, perceptions, and preferences* of user's mobility choices toward dockless bike share and the *associated impacts* on other modes of transportation as well as the local economy.

The project originally aimed to (1) understand the perceptions, attitudes, and user's mobility choices toward dockless bike-sharing services, (2) develop advanced analytics and machine learning algorithms to uncover patterns associated with mobility choice, activity-travel, and additional spending related to dockless bike sharing, and (3) empirically evaluate if and how the introduction of the dockless bike-sharing services influences public transit ridership and business sales. COVID-19 in the early 2020 led to widespread lockdowns in many countries and significantly limited people's travel behaviors. Given the significant disruption of COVID-19 on travel and mobility, we slightly revised the research direction with the new research questions focused on (1) how COVID-19 influenced people's travel behaviors and patterns, especially dockless bike sharing and (2) how COVID-19 changed the perception and attitude of dockless bike sharing.

[1] For example, Lime is an American transportation company that runs dock free pedal bikes, e-assist bikes, and electric scooters in various cities. Founded in January 2017, Lime launched services in over 70 markets across the United States in a short period of time. In July 2018, Uber announced that it is investing in Lime as part of a deal led by Alphabet, which values Lime at $1.1 billion. As part of the deal, Uber plans to promote Lime services in its mobile application (Newcomer and Stone, 2018).

DATA COLLECTION

During the initial stage of the project, the research team developed a Qualtrics survey. The survey consists of three sections. The first section collects respondents' demographic and socioeconomic attributes (e.g., gender, age, ethnicity, education attainment, household income, home cross streets, car ownership, occupation, employment status). The second section collects data on respondents' choice and preference of mode of transportation, major daily trip destination, competing destination sites (e.g., restaurants), and the key factors affecting their destination choices. The third section focuses on perception, attitude, and usage of dockless bike sharing.

We launched the survey in June 2020. Due to COVID-19, people have significantly changed their travel behavior with very minimal respondents indicating their usage of dockless bike sharing. The overall pattern during the initial stage of COVID-19 was that people significantly reduced their daily trips with many preferring to stay at home all day long. In March 2021, Arizona Governor Doug Ducey signed an administrative law lifting all state COVID-19 restrictions, which denotes the final phase of the pandemic in Arizona. Given this, the research team conducted two waves of surveys during and after the pandemic, with the first round of survey collected from June to October in 2020 and the second round from August to December in 2021 to examine the impact of COVID-19 on people's daily activity-travel, especially on the usage of dockless bike sharing and their change of perception and attitude of dockless bike sharing. We collaborated with Qualtrics and distributed the survey in Maricopa County, Arizona. In total, we collected 376 valid responses in the first round of survey and 598 in the second round.

DATA ANALYSIS AND FINDINGS

Spatial distribution pattern

Based on the cross streets information, we combined the spatial tools in Google Earth and ArcMap to geocode all respondents' home and activity sites. To understand human mobility patterns, we used the Standard Deviational Ellipse method to first investigate where people started their trips. Standard Deviational Ellipse is widely used in spatial analysis to capture point data's spatial distribution patterns. We divided the respondents into four groups based on their travel modes: Personal Vehicle (PV), Public transit (PT), High mobility service (HMS), and Human power transport (HPT). PV contains those who drive private cars and mopeds; PT includes those who take buses and light rails; HMS refers to those who use rideshare, taxis, and bike-sharing services; and HPT consists of those who ride bikes or walk. Figure 1 shows the spatial distribution of respondents' trip origins. The results reveal that because of the high mobility of PV, those who travel by personal vehicles are more widely distributed than other categories. Those who travel by public transit are more concentrated in the city center to have higher PT accessibility.

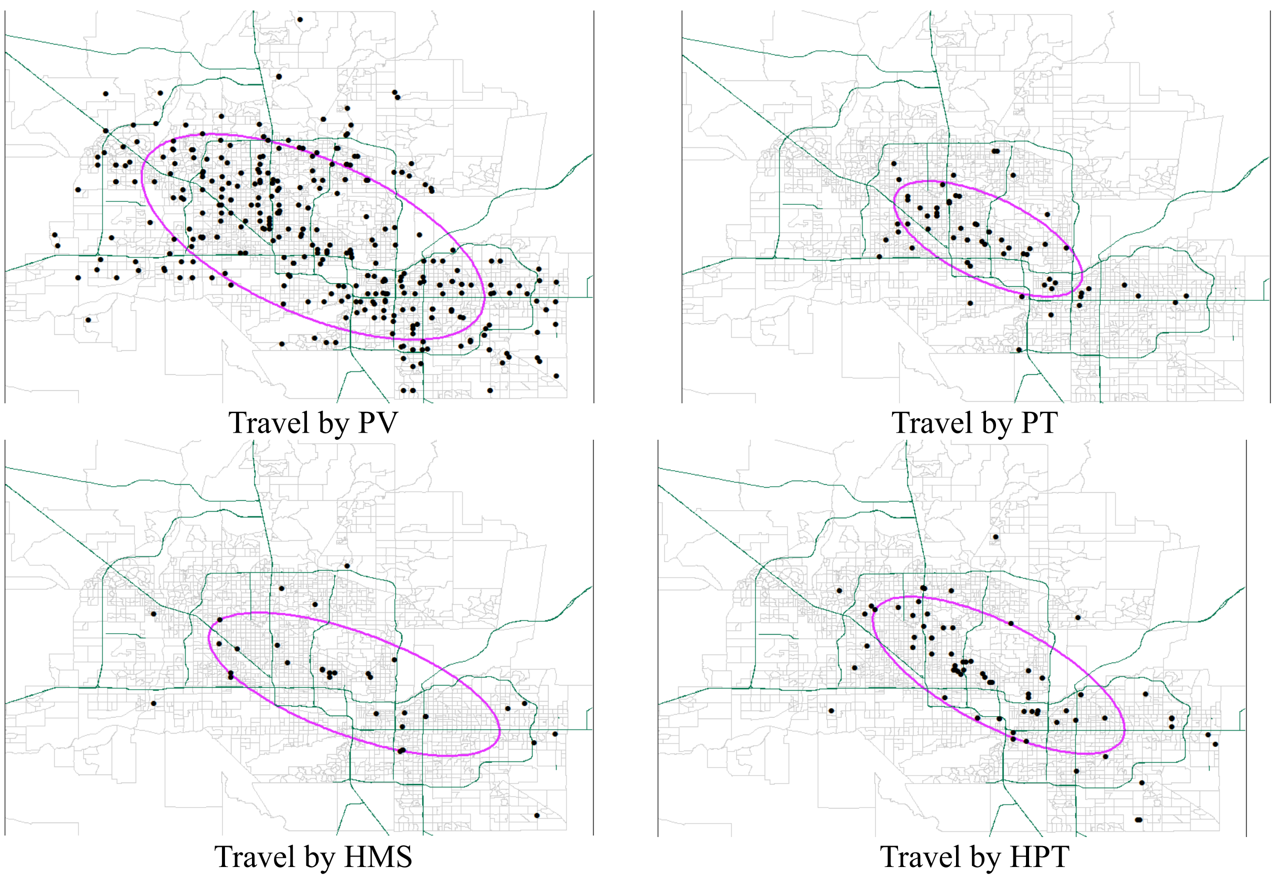

Figure 1 Spatial Distribution of Origin of Travel across Four Travel Modes

Travel distances

In addition to the origin of travel, we also calculated the total travel distance as well as the travel distances between every stop that a respondent made during their daily trips. Tables 1 and 2 summarize these results. Generally speaking, those who travel by personal vehicle (PV) tend to travel longer, both during and after the pandemic. In contrast, public transit (PT) users have shorter travel distances than those using private vehicles (PV). Travel by human power transport (HPT) is the shortest after the pandemic but is longer during the pandemic. We believe that, during the pandemic, people try to avoid contact with other people and prefer human power travel mode. Hence the associated travel distances by HPT are more extended during the pandemic.

Table 2 summarizes the travel distances between every stop. It is clear that, during the pandemic, people traveled shorter and stopped at fewer sites, no matter which transport modes they chose. Additionally, people reduced taking public transit or shared vehicles. Instead, they walked more and preferred private vehicles. These findings are consistent with those in Table 1.

Table 1 Total Travel Distances (in Kilometers) during and after Pandemic

Travel modes	**1st round survey total distances**			**2nd round survey total distances**		
	Mean	Median	SD	Mean	Median	SD
PV	24.20	16.23	25.45	33.55	20.41	61.85
PT	10.25	10.25	NA	17.28	12.23	17.32
HMS	3.39	3.39	NA	21.56	6.72	44.22
HPT	11.75	3.57	19.67	10.88	3.73	15.69

Table 2 Travel Distances (in Kilometers) between Stops during and after Pandemic

1st Round	**Distance for stop 1**			**Distance for stop 2**			**Distance for stop 3**			**Distance for stop 4**			**Distance for stop 5**		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
PV	11.57	8.16	9.94	7.39	3.88	7.59	9.49	7.32	8.10	9.60	4.89	15.24	4.63	3.36	4.79
PT	5.12	5.12	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
HMS	1.73	1.73	NA	1.29	1.29	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
HPT	5.42	1.79	9.444	1.20	0.91	1.11	2.50	2.50	NA	0.87	0.87	NA	NA	NA	NA

2nd Round	**Distance for stop 1**			**Distance for stop 2**			**Distance for stop 3**			**Distance for stop 4**			**Distance for stop 5**		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
PV	14.38	8.87	28.91	13.20	9.04	19.86	9.40	5.66	9.27	10.69	6.77	10.40	12.27	12.16	8.65
PT	8.02	5.10	8.44	8.03	7.16	6.22	4.83	2.25	8.01	1.07	0.89	0.95	1.12	1.12	NA
HMS	8.14	3.34	11.21	10.23	3.35	12.71	21.59	21.59	17.27	NA	NA	NA	NA	NA	NA
HPT	4.53	1.30	7.07	6.82	2.00	8.17	3.86	1.30	5.76	1.31	1.10	0.87	1.41	0.79	1.19

Association Rule Analysis

An association rule analysis was applied to examine the similarities and dissimilarities of travel behaviors between the two pandemic stages. Association rule analysis discovers the rules that have strong relationships between variables in a large dataset. We applied this method to determine which activity combinations happened most during and after the pandemic. The results show that travel behaviors significantly differ during and after the pandemic. Table 3 lists all the significant ($\alpha > 0.95$) association rules. Compared to the travel behaviors during the pandemic, people engaged in more diverse activity patterns after the pandemic. The origin and destination do not necessarily occur at home. People have also resumed eating out, exercising, and working in public.

Table 3 Association rules during the two different stages

During the pandemic	**After the pandemic**
Home → Accompany another person	Personal business → Eat out
Major shopping → Home	Everyday shopping → Picked up or dropped off passengers
Home → Picked up or dropped off passengers	Major shopping → Exercise
	Major shopping → Work
	Picked up or dropped off passengers → Work

Destination Selection Analysis

We designed choice preference related questions for four types of activities: eating out, everyday shopping, exercise, and major shopping. We collected people's perceptions about the factors such as price, quality, environment, and travel distance that influence their choice of activities.

1. *Eating out*

At the early stage of COVID-19, instead of visiting a restaurant with low prices, people tended to select restaurants with price just right (62%), high quality of the product and service (67%), good environment (56%), and close to where they travel from (50%). While during the late stage, there was an increased percentage of respondents going to restaurants with mediocre environment and with low prices.

Table 4 Respondents' evaluation on eating out destinations

		Price			Quality of product/service			Environment			Distance to where I travel from		
		Low	High	OK	Low	High	OK	Good	Bad	OK	Closer	Further	Equal
During Pandemic	Agree	32%	6%	62%	6%	67%	34%	56%	3%	38%	50%	30%	24%
	Disagree	32%	47%	12%	70%	12%	22%	9%	65%	21%	28%	45%	32%
	Neutral	35%	47%	26%	24%	21%	44%	35%	32%	41%	22%	24%	44%
After Pandemic	Agree	57%	18%	72%	22%	58%	39%	60%	16%	43%	61%	28%	42%
	Disagree	15%	51%	6%	61%	10%	19%	6%	61%	16%	18%	55%	24%
	Neutral	28%	31%	22%	16%	31%	42%	34%	22%	40%	21%	16%	34%

We also analyzed how the evaluation on eating out destinations varied over different population groups (by gender, age, education level, and transportation mode). In general, respondents in different groups had similar preferences when selecting eating out destinations, but there are also some differences. Females paid more attention to the dining environment at the early stage of

COVID-19 compared with male respondents. At both the early and late stages, male respondents tended to visit restaurants with lower prices. People in the 26-35 age group tended to visit places with the lowest price and paid less attention to the quality of the product and service and the environment. Highly educated people paid less attention to prices when selecting restaurants. Pedestrians are more likely to select close restaurant at the expense of the dining environment to some extent.

2. *Everyday shopping*

Similar to the reasons of selecting eating out destinations, when people select a place to conduct everyday shopping, they prefer places with low or ok price, high quality, good environment, and as close as possible. At the early stage of COVID-19, 60% of the respondents selected a store with good environment, while the percentage decreased to 52% during the late stage of COVID-19.

Table 5 Respondents' evaluation on the everyday shopping destination

		Price			Quality of product/service			Environment			Distance to where I travel from		
		Low	High	OK	Low	High	OK	Good	Bad	OK	Closer	Further	Equal
1st Round	Agree	61%	5%	65%	5%	63%	15%	60%	3%	26%	49%	18%	36%
	Disagree	2%	72%	0%	69%	0%	21%	8%	72%	15%	22%	50%	28%
	Neutral	37%	23%	35%	26%	37%	64%	33%	26%	59%	29%	33%	36%
2nd Round	Agree	62%	11%	59%	15%	53%	39%	52%	11%	45%	72%	10%	39%
	Disagree	11%	58%	7%	55%	10%	14%	9%	68%	13%	12%	67%	23%
	Neutral	27%	31%	34%	30%	37%	47%	39%	21%	42%	16%	23%	38%

In terms of preference variations, there is no significant difference between age groups, education level, and modes of transportation. As for gender, during the initial stage, female respondents are more likely to visit a store with better environment and acceptable price; while male respondents pay attention mainly to price. However, in the late stage of COVID-19, female respondents paid more attention to price.

3. *Major shopping*

When conducting major shopping, more people visited stores with acceptable price, high quality of products, good environment, and closer to where they traveled from. There are only 10 major shopping records in the first round data collection, so we didn't include the statistic in Table 6. Also because of the limited records reporting the major shopping activity, we didn't conduct the comparison over different population groups.

Table 6 Respondents' evaluation on major shopping destinations (only second round survey data)

	Price			quality of product/service			Environment			Distance to where I travel from		
	Low	High	OK	Low	High	OK	Good	Bad	OK	Closer	Further	Equal
Agree	63%	17%	69%	9%	63%	43%	71%	9%	37%	66%	14%	29%
Disagree	20%	54%	9%	66%	6%	6%	9%	74%	3%	14%	66%	31%
Neutral	17%	29%	23%	26%	31%	51%	20%	17%	60%	20%	20%	40%

4. *Exercise*

When selecting a place to exercise, people usually visited a place with high quality of service, good environment, and low/OK price. Compared with the early stage, during late stage of COVID-19, people are more likely to visit a closer place. Because of the limited records reporting the exercise activity, we didn't conduct comparison over different population groups.

Table 7 Respondents' evaluation on the exercise destination

		Price			Quality of product/service			Environment			Distance to where I travel from		
		Low	High	OK	Low	High	OK	Good	Bad	OK	Closer	Further	Equal
1st Round	Agree	50%	0%	46%	15%	69%	23%	57%	0%	31%	31%	38%	0%
	Disagree	14%	54%	8%	62%	31%	23%	7%	69%	23%	46%	23%	23%
	Neutral	36%	46%	46%	23%	0%	54%	36%	31%	46%	23%	38%	77%
2nd Round	Agree	67%	4%	67%	13%	54%	42%	67%	0%	29%	58%	25%	13%
	Disagree	13%	79%	0%	54%	13%	8%	0%	71%	4%	17%	46%	29%
	Neutral	21%	17%	33%	33%	33%	50%	33%	29%	67%	25%	29%	58%

Perceptions and attitudes about various modes of transportation

In terms of people's attitude towards shared mobility, more than 50% of the respondents thought shared mobility was useful (52% in the first round data collection and 54% in the second round), and 74% of the respondents thought shared mobility was environment friendly (based on both rounds of survey). At the initial stage of COVID-19, 80% of the respondents felt uncomfortable being around people when traveling, and the percentage decreased to 58% during the late stage. To avoid being around people, people avoided using public transportation and ride share service such as Uber and Lyft. However, they didn't drive themselves more often or switch to shred mobilities. In general, people limited their travel plans during COVID-19 (79% during the early stage and 54% during the late stage).

CONCLUSIONS

Shared mobility represents an innovative transportation strategy that allows users to make short distance trips on an as-needed basis without the hassle of traditional transportation modes. The recent rise of on-demand ride-sharing systems (Uber, Lyft, Lime, Mobike, Bird, Jump) is having transformative impacts on travelers' attitudes, mobility choices, and behavioral responses to a wide range of daily activities.

In this study, we surveyed the general public to understand the perceptions, attitudes, and user's mobility choices toward dockless bike-sharing services. Due to the disruptions caused by COVID-19, we conducted two rounds of surveys with one during the pandemic (from June to October 2020) and the other after the pandemic (August to December 2021). Our analysis reveals several interesting patterns about spatial distributions of the origin of travel, travel distances, as well as trip lengths across various modes of transportation. Additionally, we analyze trip chaining activities using an association rule mining technique and highlight various activity patterns after the pandemic. Finally, we evaluate the factors (price, quality, environment, and travel distance) that can influence people's decision choice of various activities such as eating out, shopping, and excise.

This study contributes to the spatial interaction literature. Spatial interaction takes a variety of forms, but usually involves movement of people, goods, or information over physical space that results from a decision-making process (Fotheringham, 2001). The rapid advancement of technology and the digital revolution have significantly empowered consumers in their decision-making process. It is therefore important to incorporate key elements from the digital space and examine how those elements influence spatial flows as well as the choice behavior of consumers in the physical world. In that regard, we hope this study offers insights about some of the underlining factors in the digital space that can generate a better understanding of spatial interaction and further calibrate spatial interaction models. This study also has implications on consumer behavior models, which examines various factors in a consumer's decision choice. Some of the factors (such as consumer demographics, seasonality and day of the week, location) are difficult to control while others (including quality, price, environment and atmosphere) are relatively easier to change. This study highlights a few important observations to earlier decision choice models in the context of shared mobility service.

It is also important to highlight that the phenomenon of shared mobility driven by technologies, data, and digital platforms has opened the gate for scholars in operations management (OM) to push OM knowledge boundaries on inventory management, resource allocation, facility location, scheduling, dynamic pricing, etc. For example, when examining resource allocation and facility location decision problems of shared bike operations, researchers have proposed both user-based as well as operator-based approaches to tackle bike imbalance, i.e., reestablishment of the number of bikes at sites to desired quantities (Waserhole et al. 2013; Dell'Amico et al. 2014; Schuijbroek et al. 2017). For bike-sharing service providers, attempting to rebalance the system by moving bikes from full to empty stations represents one of the largest operational challenges (Freund, et al. 2018).

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