Examining Market Segmentation to Increase Bike-Share Use: The Case of the Greater Sacramento Region

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A Research Report from the National Center for Sustainable Transportation

Hossain Mohiuddin, University of California, Davis
Dillon Fitch, University of California, Davis
Susan Handy, University of California, Davis

National Center for Sustainable Transportation

UC DAVIS Institute of Transportation Studies

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16. Abstract

Bike-share systems are proliferating across the US and could expand opportunities for those most underserved by the transportation system. A deeper understanding of current bike-share users could enable the expansion of these services and their benefits to a larger population. With the aim of deepening this understanding, this study uses data from household and bike-share user surveys in the Sacramento region to perform behavioral modeling and market segmentation. The results show that although individuals with low incomes and students are less likely than other demographic groups to use bike-share, they use it more frequently if they do use it. Individuals who regularly use multiple modes of travel also use the service frequently. The initial adoption of the service by transport-disadvantaged groups can play a vital role in the continued and frequent use of the service. The market segmentation analysis shows that low-income individuals, students, and zero-car individuals use the service frequently for commuting and a variety of non-commuting purposes. The occasional users of the bike-share service are mainly those with higher incomes and individuals who have access to a personal car. Another market segment consists of non- and infrequent-personal bike users; however, that segment is using the bike-share service at a greater rate for different purposes compared to regular bicyclists. This suggests that bike-share may fill an important travel gap and act as a lever for increasing bike travel for some users. Overall, the results provide detailed bike-share market information that can be used to tailor urban transport policies. The results also suggest that if the user base for bike-share programs were expanded to reach even more low-income individuals, students, and multi-modal travelers, greater environmental sustainability benefits would be achieved.

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Hossain Mohiuddin, Transportation Technology and Policy Program, Institute of Transportation Studies, University of California, Davis

Dillon Fitch, Institute of Transportation Studies, University of California, Davis

Susan Handy, Institute of Transportation Studies, University of California, Davis

TABLE OF CONTENTS

List of Tables

List of Figures

Examining Market Segmentation to Increase Bike-Share Use: The Case of the Greater Sacramento Region

Highlights

- We use behavioral modeling and market segmentation approaches to identify opportunities for growing demand while improving equity
- We segmented bike-share users based on their socio-demographics and mode use behavior; attitude towards different travel modes and their surrounding environment for biking; concern regarding different aspects of travel; and perception of the bike-share service
- Our models show that although individuals with low incomes and students are less likely than others to use bike-share, they use it more frequently compared to others when they do use it
- Initial adoption of bike-share by transport-disadvantaged groups can play a vital role in the continued and frequent use of the service
- Modality style analysis shows that a group of multi-modal travelers who use ridehail, carshare, active modes, and transit also use the bike-share at a much greater frequency than others.
- A market segment that consists of non- and infrequent-personal bike users who mostly have low incomes and no access to a personal car is using the bike-share at a greater rate for different trip purposes compared to regular bicyclists.
- Based on our findings, we suggest increasing the number of bicycles available and expanding the market share among the following groups: low-income populations, students, transit users (especially infrequent transit users), people who do not own cars, frequent users and non-users of ridehailing services, and women. This could assist in simultaneously addressing social equity and boosting the demand for bike-share.

EXECUTIVE SUMMARY

Bike-share services have the potential to aid transportation sustainability: they can be used as an access and egress mode for public transit, provide mobility options to carless individuals, enable individuals to become less car-dependent, and substitute for higher emitting modes. As cities do not have much control over the operation of these services, providing adequate access to the service for transport disadvantaged groups is a challenge for them. Given the potential benefits of micromobility services, researchers can assist cities in leveraging these private investments for social good by helping them understand the different segments of bike-share users as a step toward expanding ridership.

With the goal of informing cities' efforts, we use behavioral modeling and market segmentation approaches to identify opportunities for growing demand while improving equity. A bike-share system improves social equity if the service is available to segments of the population who struggle to afford transportation and who cannot own or use a personal car. In this study we evaluate groups with clear disadvantages, such as low-income individuals (who in this study we define by a personal income less than $25,000 or household income less than $50,000), and groups with potential disadvantages such as carless individuals/households, transit users, carshare users, and student users. Using data from household and bike-share user surveys in the Sacramento region, we analyzed the influence of socio-demographic and other travel and mode-related factors on the initial adoption and continued use of the service. We also segmented bike-share users based on their socio-demographics and mode use behavior; attitude towards different travel modes and their surrounding environment for biking; concern regarding different aspects of travel; and perception of the bike-share service. Due to the low responses from the Black residents and users, we did not focus on race in this analysis.

Statistical modeling showed that although low-income individuals and students are less likely to use bike-share, they use it more frequently compared to others when they do use it. Individuals who regularly use multiple modes of travel also use the service frequently. The results indicate that the initial adoption of the service by transport-disadvantaged groups can play a vital role in the continued and frequent use of the service.

Our market segmentation of bike-share users shows that the use of the service is mostly driven by the need for transportation rather than attitudes regarding different modes and perceptions of bike-share. Psychometric segmentation shows that a positive attitude towards bikes and a negative attitude towards driving are not associated with frequent use of the service. Also, more positive perceptions of bike-share are not associated with more frequent use of the service. Rather, we found that low-income and zero-car individuals are using the service frequently even though that segment has a less positive attitude towards biking and a less positive perception of different aspects of the bike-share system compared to others. This suggests that the use of the service is driven by limited access to personal cars and by affordability.

The market segmentation analysis incorporating travel behavior shows that low-income individuals, students, and zero-car individuals use the service frequently for commuting and a variety of non-commuting purposes. The occasional users of the bike-share service are mainly those with higher incomes and individuals who have access to a personal car. Also, among the bike-share users, two types of multimodal groups exist: one group that mainly uses active modes (i.e., walking and bicycling) for commuting purposes and another group that uses a combination of ridehailing, transit, carshare, and active modes. The former group uses the service at a greater-than-average frequency, while the latter group uses the service at a much greater frequency. There is also a market segment that consists of non- and infrequent-personal bike users who mostly have low incomes and no access to a personal car; however, that segment is using the bike-share service at a greater rate for different purposes compared to regular bicyclists. This suggests that bike-share may fill an important travel gap and act as a lever for increasing bike travel for some users.

The results suggest that if the user base for bike-share programs were expanded to reach even more low-income individuals, students, and multi-modal travelers, greater environmental sustainability benefits would be achieved. These findings suggest that increases in demand and social equity can be achieved simultaneously, counter to the common strategy of concentrating bike-share service in areas with higher incomes to maximize demand. Based on our findings, we suggest increasing the number of bicycles and further expanding the market share among the following groups: low-income populations, students, transit users (especially infrequent transit users), people who do not own cars, frequent users and non-users of ridehailing services, and women.

These approaches will assist in simultaneously addressing social equity and boosting the demand for bike-share. Approaches for achieving an increase in bike-share users for different socio-demographic groups can mutually work together. We also discuss future research directions based on our work. The findings from this study can be useful in efforts to achieve social equity in bike-share service operations.

Introduction

Project Purpose

The recent emergence of the dock-less electric bike- and scooter-shares have allowed a growing number of US cities to look toward bike/scooter share to improve environmental, social, and health outcomes from the transportation system. *Micromobility services*—used throughout this report to refer to bike- and scooter-share services but not personally owned bikes and scooters—have proved popular in many cities (NACTO, 2019). However, little is known about the preferences, attitudes, and decision processes of users, and even less is known about the barriers for non-users. The survey data collected by UC Davis on the travel patterns of both users and non-users of the greater Sacramento area bike- and scooter-share service offer a unique opportunity to address these research gaps. Prior analysis suggests bike/scooter-share may be an important strategy for addressing many statewide goals (e.g., SB 375 directs the setting of regional targets for reducing greenhouse gas (GHG) emissions; and AB 32 aims to reduce greenhouse gas emissions from all sources throughout the state) (Chen et al., 2022; D'Almeida et al., 2021; Magill, 2014). Given this evidence, cities/regions need strategies to encourage and support more bike-share use. Our purpose in this project is to better understand the market for bike-share to guide cities/regions in developing these strategies.

Although micromobility services were initially withdrawn from the Sacramento area and many other areas due to shelter-in-place and business closures from the COVID-19 pandemic, the potential for micromobility services post-pandemic remains. Not only were micromobility services rapidly growing before the pandemic, but considering contagion concerns from public transit and ridehailing, micromobility services have the potential to attract new riders. There is already evidence in some markets that e-scooter trips are much longer than before, thereby suggesting that micromobility services may become a more essential travel mode for some people (Fehrenbacher, 2020) . The potential for micromobility services to re-emerge as an important transportation service along with the need for strategies to improve the sustainability of our transportation systems indicates the need for understanding the micromobility service market.

Background of the Study

Many cities around the world have embraced bike-share systems in the last decade as an important mobility option that can help them achieve sustainability goals (Fishman et al., 2013) Bike-share has the potential to be an attractive travel mode for several trip purposes (Fitch et al., 2020) Bike-share systems can also play a role in supporting rather than competing with transit by providing an option for the first or last mile of a trip using transit (Mohiuddin, 2021; Shaheen and Chan, 2016). Additionally, after the introduction of bike-share, bicycling increased among the users of the bike-share (Fitch et al., 2021a). Reflecting this potential, these systems have attracted substantial ridership, even in the U.S. (National Association of City Transportation Officials, 2020).

Evidence from national travel surveys shows that in many cases people make multiple trips of short length on a daily basis, especially for school, shopping, and personal errands (FHWA, 2009) These trips have the greatest potential to be made by bike, e-bike, and e-scooter. Studies show the potential for micromobility services to reduce car travel in the US (Lime, 2018; PBOT, 2018), leading to reductions in greenhouse gas (GHG) emissions, air pollution, congestion, and noise pollution, and increased physical activity (Garrard et al., 2012b). Bike-share services are creating opportunities for cities to decrease car travel. Given the potential benefits of micromobility services, researchers can assist cities in leveraging these private investments for social good by helping them understand the different segments of bike-share users as a step toward expanding ridership.

Social equity is an important consideration in efforts to expand bike-share services. One study found that bike-share operators, in an effort to boost demand, tended to locate new stations near wealthy neighborhoods (Duran-Rodas et al., 2021). Similar findings are seen in the case of the New York Citibike system where stations are generally located in wealthier neighborhoods (Babagoli et al., 2019). Another study across different cities in the US shows considerable differences in service access based on race, income, and education level (Ursaki and Aultman-Hall, 2016). Inequity in the bike-share systems stems not only from location but also from the cost of access, lack of payment options, and the need for bank and credit card accounts for most current payment systems (McNeil et al., 2018). But bike-share has ample potential to serve low-income communities. Bike-share systems can provide mobility options to carless travelers and transit-dependent populations. Emphasizing the role of bike-share as a complement to transit can help to expand travel options for those dependent on transit. The most recent bike-share systems have taken the form of dock-less electric-assisted bicycles (e-bikes), offering the potential to attract even more riders, given the greater speed of travel and flexibility in pick-up and drop-off locations. Dockless bike-share systems provide more flexibility in defining service areas and may improve access to bike-share relative to earlier systems constrained by the location of bike-share stations (Qian et al., 2020a). However, dockless systems need proper rebalancing policies to ensure equitable access. Proper geofencing policies connected to the operating permit can help to ensure equitable distributions of bikes (Moran, 2021). It is important to understand the bike-share market with reference to social equity to grow the service in a more just and sustainable way.

Research Design

Research Questions and Approach

In this report we focus on three primary research questions:

> *"What socio-demographic, travel-and-mode related factors influence initial adoption and continued use of bike-share?"*
>
> *"What market segments exist among bike-share users?"*
>
> *"How can a city grow micromobility demand while addressing social equity?"*

A bike-share system is equitable if the service is available to segments of the population who struggle to afford transportation and who cannot own or use a personal car. In this study we evaluate groups with clear disadvantages such as persons with low incomes (defined in this study as a personal income less than $25,000 or household income less than $50,000), those without cars individuals/households, transit users, carshare users, and students. We use both behavioral modeling and a market segmentation approach to address the research questions. Thus, we conduct (a) analyses of the socio-demographic and mode use factors that influence the decision to use bike share and the frequency of use, and (b) segmentation of the bike-share market by demographic, psychometric, and behavioral factors.

Study Area Context

The Jump-operated electric bike-share service in the greater Sacramento region launched in the summer of 2018 and comprised approximately 900 electric-assist bicycles (e-bikes) as of November 2018. By May 2019, the number of e-bikes increased to closer to 1,000 and was available in Davis, Sacramento, and West Sacramento. Also, 100 e-scooters were available in Sacramento and West Sacramento but not Davis. Because the service is predominantly e-bikes (and not e-scooters), we focus specifically on analyzing the bike-share service rather than the overall micromobility service. The service covered an area of approximately 50 square miles, though this was not all contiguous. Davis, in particular, is separated from West Sacramento by about 10 miles. Davis, unlike West Sacramento and Sacramento, has a history of having a relatively high proportion of bicyclist in the population and of accommodating bicycles in transportation design (Buehler and Handy, 2008).

Data Collection

In this study, we use data from a two-wave survey of Jump bike-share users and from a parallel household survey of residents before and after the bike-share arrived. All survey data were collected prior to the COVID-19 pandemic. The user survey was a two-wave longitudinal survey (with some panel refresh) of bike-share users in October 2018 and May 2019. These participants were recruited through interception and advertising. The household survey data includes a repeat cross-sectional survey of “before” bike-share data (2016) and “after” bike-share data (May 2019) based on a geographically stratified random sample. (See (Fitch et al., 2021b) for specific survey design details.) From this household repeat cross-sectional survey, we use only the data from the “after” survey that measured whether respondents had ever used the bike-share service. The timeline of the surveys is given in Figure 1.

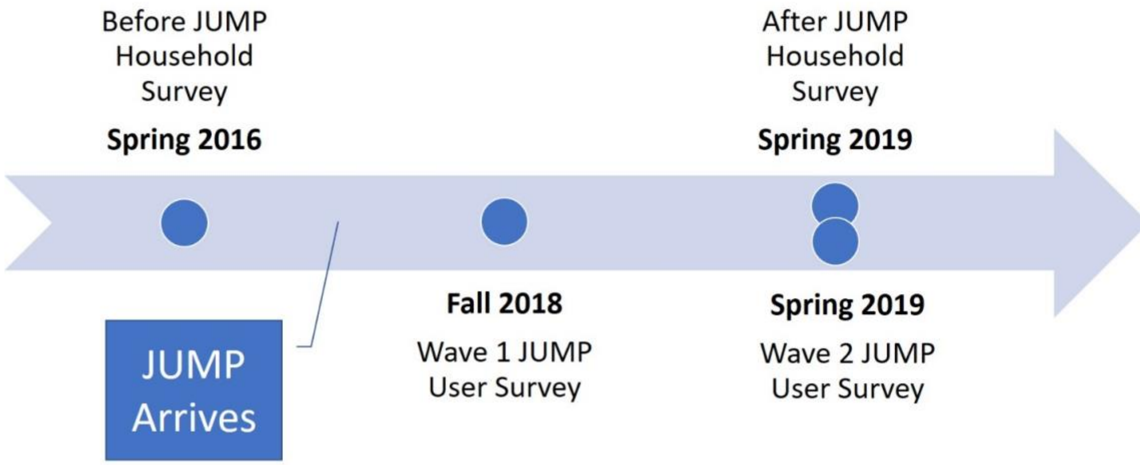

Figure 1. Timeline of household and bike-share user surveys with respect to bike-share service arrival

In both the household and user surveys, we asked questions about access to and use of different transportation modes, attitudes towards bicycling and other aspects of transportation, perceptions and use of the Sacramento area bike-share, and socio-demographic characteristics including income and race/ethnicity. The sample characteristics for both household and bike share users' surveys are shown in Table 1.

Table 1. Characteristics of the Household (HH) Survey and Bike-share User Survey Samples

Variable		HH Survey (After bike-share)	Bike-share User Survey	Study Area Characteristics
Sample Size	Wave 1		462	
	After / Wave 2	831	269 (140 panel)	
Response Rate			NA	
	Wave 2	10%	NA	
Student		8%	25%	17%
Race	White	78%	65%	48%
	Black	4%	4%	10%
	Hispanic	9%	13%	25%
	Asian	9%	18%	17%
Education Status	College education	76%	76%	67%
	No college education	24%	24%	33%
Age	15 to 30	16%	40%	
	30 to 40	19%	31%	34 years (Mean)
	40 to 50	13%	17%	
	Older than 50	52%	12%	
Gender	Woman	55%	41%	51%

Variable		HH Survey (After bike-share)	Bike-share User Survey	Study Area Characteristics
Income	Low (household < $50,000 or personal < $25,000)	15%	20%	45%
	Middle (household < $150,000 or personal <$100,000)	60%	57%	29%
	High (household >$150,000 or personal >$100,000)	25%	23%	26%
Transit User	Non-user	83%	71%	
	Infrequent User (1-2 days in a week)	7%	11%	
	Moderate User (3-4 days in a week)	4%	7%	
	Frequent User (≥ 5 days in a week)	6%	11%	
Bike User	Non-user	38%	4%	
	Infrequent User (a few times per year)	16%	11%	
	Moderate User (a few times per month)	18%	23%	
	Frequent User (weekly or daily)	28%	63%	
Ridehail user	Non-user	30%	8%	
	Infrequent User (a few times per year)	41%	36%	
	Moderate User (a few times per month)	24%	45%	
	Frequent User (weekly or daily)	5%	11%	
Carshare user	Non-user	91%	82%	
	Infrequent User (a few times per year)	6%	9%	
	Moderate User (a few times per month)	2%	8%	
	Frequent User (weekly or daily)	1%	2%	
Zero car Household/User		5%	14%	8%

Source: Household survey and bike-share user survey and US census

Data Analysis Methods

Prior approaches to bike-share analysis

Researchers have previously used survey data for bike-share behavioral modeling (Bachand-Marleau et al., 2012; Chen et al., 2020) and system-level data (Li et al., 2020) for demand modeling. Most bike-share demand studies have focused on the socio-demographic and land use characteristics surrounding docking stations (Rixey, 2013; Wang et al., 2021, 2015). Demand models generally combined data from the bike-share system with socio-demographic data from the census (Faghih-Imani et al., 2017; Faghih-Imani and Eluru, 2016), while adoption and frequency models use data from surveys (Bachand-Marleau et al., 2012). We take the latter approach in this study to better understand the person-level characteristics and behavior, which in the modeling of aggregate data must be assumed.

Several simple and basic approaches to market segmentation have been used in bicycle-related studies. For example, Deakin (1985) segmented bicyclists based on socio-demographics and travel behavior; Bergstrom and Magnusson (2003) clustered bicycle travelers based on their use frequency in different seasons (winter and summer); Heinen et al. (2011) segmented the commuting trips by lengths and explored attitudes associated with the choice of bicycling to work, etc. However, these segmentation analyses do not account for the fact that individuals with similar socioeconomic or activity characteristics can make different transportation choices (Li et al., 2013), an oversight that can oversimplify the market segments (Anable, 2005).

Evidence suggests that apart from socio-demographics, attitudes towards bicycling safety and convenience influence bicycle use (Noland and Kunreuther, 1995). For instance, a positive attitude toward bicycling increases the likelihood of using bikes for commuting (Dill and Voros, 2007), and a negative perception toward cars spurred bicycling (Stinson et al., 2005). Gatersleben and Appleton (2007) found that attitudes toward bicycling and the perception of barriers affected bicycling use. A study by Heinen et al. (2011) reported that the attitudes had a strong impact on the choice of bicycle for commuting. That same study also showed that socio-demographics can explain a limited portion of travelers' attitudes. Based on the findings of these studies, we include socio-demographics, individuals' attitudes towards different modes, and individuals' perceptions towards bike-share services to segment the market to better understand different user groups.

In general, clustering is the most widely used method for market segmentation in consumer studies (Dolničar, 2003). These studies show that clustering can group homogeneous travelers and produce distinct market segments. Some studies have divided customers into groups according to researcher-specified segments to explore their associations with behavior (Bergström and Magnusson, 2003; Elgar and Bekhor, 2004; Heinen et al., 2011). However, this type of segmentation is based on researchers' perceptions that may not reflect the inherent characteristics of segments that are unknown to researchers. To overcome those limitations, several studies have used the statistical clustering method to segment the market (Anable, 2005; Li et al., 2013; Outwater et al., 2003; Ryley, 2006). In our study, we used a statistical clustering method to segment the market based on the selected factors collected from the survey (i.e., socio-demographics, attitudes towards different travel modes, and perception of bike-share service).

We use data from surveys of both users and non-users of the bike-share system in the greater Sacramento area, as reported in prior studies done by Fitch et al. (2020b). Using that data, we estimated a series of statistical models to identify which socio-demographic and mode use factors have strong associations with bike-share use as a starting point for segmenting the bike-share market. Then, we performed cluster analysis on the bike-share user data. Comparing a series of cluster analyses highlights characteristics of different user groups that can be targeted by policy or marketing. For example, if a psychographic segmentation shows a class of people likely to use bike-share in a geographic area that has poor bike-share availability, an obvious strategy is to allocate more bikes to that area. Or if that same psychographic class overlaps with a low-income class, a bike-share subsidy program may make sense. We then focus on analyzing the market segments for whom transportation equity is a concern: low-income status, zero-car households, student status, and transit and car-share users. We examined the relationship between segments and bike-share ridership with reference to selected socio-demographics and mode user groups. The results provide insights that may help cities consider strategies to increase bike-share demand in a way that enhances social equity.

Bike-share Behavioral Modeling

We used generalized linear regression models of *having used bike-share* and the *frequency of bike-share use* to better understand the factors influencing initial adoption and continued use of bike-share.

Modeling "Used bike-share"

In this analysis, we developed a model using the data from the "after" household survey. The dependent variable of the model was the response to the survey question, *"Have you ever used the Jump bike-share in the greater Sacramento area?"*. This model can also be referred to as the bike-share initial adoption model. We estimated the following multilevel Bernoulli regression (binary logit) model (equation 1) to determine which factors are likely to have large effects on using bike-share:

$$\mathrm{y}_i \sim \text{Bernoulli}\ (p_i)$$

$$\mathrm{logit}(p_i) = \alpha + \alpha_{city[j]} + \sum_{m=1}^{M} \beta_m X_{mi}$$

$$\underline{\text{Priors}}$$

$$\begin{aligned}
\alpha &\sim \text{Student's t}(\,3\,,0\,,2)\\
\alpha_{person} &\sim \text{Normal}(\,0\,,\sigma\,)\\
(\beta_1, \dots, \beta_m) &\sim \text{Normal}(\,0\,,2\,)\\
\sigma &\sim \text{HalfNormal}(\,0\,,1\,) \qquad (1)
\end{aligned}$$

Where "y_i" is the binary response for observation *i*, and assumed to have a Bernoulli distribution with logit link about the linear model p_i. The linear model p_i is a function of the mean intercept α, a vector of city-level intercepts α_{city} indexed by *j* people with city level average variation σ (Standard deviation). The main parameters of focus are the "slope" parameters β_m, a vector of effects for each predictor variable X_m.

Modeling Bike-share Use Frequency

In this analysis of bike-share users, we examine the response to the question *"In the past 28 days, how many Jump [bike-share] trips did you make?"* from both waves of the bike share user survey. In this question, respondents were asked to use their phone app or online account to retrieve the exact number of trips in the past 28 days. We estimated the following multilevel negative binomial (i.e., gamma Poisson) regression model (equation 2) to predict bike-share use frequency:

$$y_i \sim \text{negbinomial}\ (p_i, \varphi)$$

$$\log(p_i) = \alpha + \alpha_{person[j]} + \sum_{m=1}^{M} \beta_m X_{mi}$$

Priors

$$\begin{aligned} \alpha &\sim \text{Student's t}(\ 3\ ,0\ ,\ 2) \\ \alpha_{city} &\sim \text{Normal}(\ 0\ ,\sigma\ ) \\ (\beta_1, \dots, \beta_m) &\sim \text{Normal}(\ 0\ ,2\ ) \\ \sigma &\sim \text{HalfNormal}(\ 0\ ,1\ ) \\ \varphi &\sim \text{Gamma}(\ 0.01\ ,0.01\ ) \end{aligned} \qquad (2)$$

All the parameters in the model of bike-share use frequency have a similar structure to that of the "using bike-share" model with the exception that these parameters are linked to the linear model through the log link (instead of logit). The one additional parameter φ ("shape") accounts for the varying effort by participants to report their true trip frequency (e.g., some people may do so by memory, others by counting trips on their phone, etc.).

For each model, we used weakly regularizing priors to guard against overfitting, and we examined the posterior predictions of each model graphically to ensure each model could roughly approximate the empirical distribution of the data. We compared a series of similar models with different predictors (not shown) such as with only socio-demographic variables, socio-demographic variables with mode use variables, socio-demographic variables with mode use and built environment variables, etc. We ended up with this structure of the behavioral model including the socio-demographic and mode use variables that relate to our research question.

To estimate each model, we used Bayesian inferences using the brms package (Bürkner, 2017) in R which is an interface for the Stan computing language (Stan Development Team, 2018). We used the default estimation algorithm (dynamic Hamiltonian Markov Chain Monte Carlo

(MCMC)) and ensured that the MCMC chains converged ($\hat{r} < 1.01$), and that the model produced no other diagnostic warnings from Stan and brms.

Missing Data

The bike-share user survey had missing values in most of the variables used in this analysis. We did not drop any respondents who responded to most of the survey because of the possibility it would bias our analysis. Studies show that the multiple imputation method is superior for handling missing data to listwise deletion (Pampaka et al., 2016; van Ginkel et al., 2020). We used multiple imputations from the chained equations (MICE) approach to impute the missing data from the study (van Buuren and Groothuis-Oudshoorn, 2011). We imputed 20 datasets and 100 iterations per dataset to ensure that the MCMC chains converged ($\hat{r} < 1.01$). We then ran all regressions on each dataset and combined the results to make inferences.

Market Segmentation Approach

Along with conducting the behavioral modeling of bike-share initial adoption and continued use, we also segmented the bike-share market using different approaches. A segment, also referred to as a *cluster* throughout this report, is assumed to be a collection of individuals all of whom are behaviorally similar from the perspective of the researcher. The rationale behind using both the modeling and segmentation approaches is that behavioral models tell a portion of the story about the marginal relationships between different personal characteristics and the frequency of bike-share use. However, because we did not have a conceptual model of interactions, we chose to use clustering to explore more complex associations that could lead to more complex regressions in the future (testing these interaction effects is beyond the scope of this study) and examine specific segments we suspected to be important.

From the behavioral perspective, individuals can be heterogenous in their use behavior of the bike-share. Consumer heterogeneity is fundamental in any marketing research as it provides the basis for segmentation, targeting of customers, and marketing of the product (Kamakura et al., 1996). This heterogeneity may arise from different aspects associated with individual characteristics. For instance, it is expected that an individual's bike-share adoption and use behavior would be different based on different socio-demographic characteristics such as gender, race, income, etc. These observable differences are called observed heterogeneity. However, research shows that heterogeneity may arise not only based on the observed characteristics of the individual but also on unobserved characteristics such as individuals' beliefs about a product, values, etc. (McFadden, 1986). Both the observed and unobserved heterogeneity affect an individual's preference for a service and ultimately lead to a choice about whether to use it. Several methods have been developed to capture those unobserved heterogeneities. In transportation surveys, a series of statements are designed to capture different aspects of attitudes and perceptions, with responses collected on a Likert agree-disagree scale. Studies show that attitudes such as pro-bike attitude, pro-car attitude, pro-transit attitude, pro-environment attitude, etc., are important determinants of mode choice (Handy et al., 2010; Kitamura et al., 1997; Kroesen et al., 2017).

We performed two different types of market segmentation analysis, namely deterministic and discovery. In the deterministic segmentation, we divided the bike-share user's frequency of using bike-share in the last 28 days into four categories and explored the socio-demographic and mode use behavior in those categories. In the discovery market segmentation approach, we further conducted both psychometric and behavioral segmentation. The psychometric and behavioral market segmentation approach is described in Table 2.

For behavioral analysis, we segmented the users based on their use of the bike-share for commuting and different non-commuting purposes. Additionally, we conducted an analysis of the modality styles of the users based on their commuting mode choice (i.e., walk, bike, transit, car, and carpool) and segmented the users based on their modality styles. Modality styles in this study refer to how frequently individuals use different modes for their commuting and non-commuting purposes. For instance, if an individual uses a car all the time for commuting and non-commuting purposes, then that individual is termed unimodal. There can also be quasi unimodal (i.e., individuals who use a car for the majority of their trips) and multimodal (i.e., individuals who use different types of modes for making their trips). In this study, modality styles are measured by their use of modes for commuting in a week. We asked individuals how many days in a week they use different modes (i.e., walk, bike, transit, car alone, and car passenger) for commuting purposes. Based on the response to these questions, we classified individuals into three modality style groups. Market segments based on modality styles are a form of behavioral segmentation since modality styles are defined by the travel behavior of the individual.

For psychometric segmentation, we conducted a series of cluster analyses using different types of latent attitudes and perception variables (Table 2). We used individual responses collected in the survey for different modes and travel-related attitude statements to conduct this analysis. We also used responses to the respondent's perceptions of bike-share. Finally, we used measures of individuals' concerns regarding travel time, cost, and environment, while making travel decisions.

Table 2. List of variables and their mean scores for travel-related attitude, perception of bike-share, travel-related concerns, and bike-share use segmentation approach*

Attitude regarding different travel modes	Mean score (on a scale of 1 to 5)
Riding a bike is fun	4.39
Riding a bike is enjoyable	4.37
Riding a bike is boring	1.76
Riding a bike is pleasant	4.36
I like riding a bicycle	4.43
Many people I know think bicycling is healthy	4.18
Many people I know think bicycling is fun	4.01
Many people I know think bicycling is safe	3.36
Many people I know think I should bicycle	3.20
I need my car to do many of the things I like to do	3.23
I need my car to carry shopping or children	3.43
I try to limit my driving as much as possible	3.54
Perception of different aspects of the bike-share service	**Mean score (on a scale of 1 to 5)**
JUMP bikes are convenient	3.53
Riding a JUMP bike is fun	3.52
JUMP bikes allow me to get where I need to go quickly	3.61
JUMP bikes are inexpensive	3.29
JUMP bikes are comfortable	3.15
JUMP bikes are heavy	3.34
It is hard to find a place to park JUMP bikes	2.91
A JUMP bike is usually available when and where I need one	2.855
How important different travel aspects are	**Mean score (on a scale of 1 to 5)**
Concern for the environment	2.70
Concern for cost	2.81
Desire to get exercise	2.66
Concern for safety from crime	3.42
Concern for safety from traffic	2.63
Desire for enjoyment	2.64
Concern for time	3.01
Desire for convenience	3.27
Use of bike-share for different purposes	**Mean score (on a scale of 1 to 5)**
Going to School	1.61
Going to Work/Commute	2.52
Going to work-related trips	2.24
Going to grocery	2.09
Going to other shopping	2.17
Going to restaurants or bars	3.03
Going to friend and family	2.20
Using bike share to connect to transit	2.34
Going to exercise	2.33
Going to other purposes	1.30

*For each statement in the table, 1 indicated "strongly disagree"; 2, "disagree", etc. Source: Bike-share user survey

In the segmentation analysis, we convert the Likert statement responses into interval-level scores and use those to perform cluster analysis. Then, we used the response scores of individuals to calculate the distance among individuals for a selected number of variables in each cluster analysis.

We use several steps to do the market segmentation: variable selection for clustering, optimal cluster number selection, conducting K-means clustering based on the optimal number of clusters and analyzing different socio-demographic and travel behavior-related variables within each cluster. We determined the number of clusters for each analysis based on the three most popular methods of clustering, namely, the Elbow method, the Silhouette method, and the Gap statistics method (Tibshirani et al., 2001). To determine the appropriate number of clusters, the Elbow method minimizes the total intra-cluster variation, the Silhouette approach measures how well the objects are placed within its cluster, and the Gap distance method compares the intra-cluster variations for different cluster sizes with reference to the null distribution of the data. Based on the results of the three-clustering methods, we decided on the final cluster number in each cluster analysis. We used the R package “cluster” for conducting these processes (Maechler et al., 2019) and the R package “psych” for analyzing the clusters (Revelle, 2015).

Limitations

Although we attempted to generate a representative sample by using random addresses in the household survey, self-selection bias is always a concern: people who choose to respond may have behavioral and attitudinal predispositions toward bike-share. This is especially true of the second wave of the household survey since the letter indicated that the survey was about the regional bike-share system.

Also, because our recruiting method for the bike-share user survey included intercepting and asking bicyclists on personal bicycles if they had ever used the bike-share system, the sample is potentially biased toward people who bicycle more regularly. The survey undoubtedly reflects some non-response biases as some individuals did not respond to some of the questions. We tried to overcome that limitation using the multiple imputation process described above.

Results and Discussion

Behavioral Modeling of Bike-share Use

The parameter estimates of the "using bike share" and bike-share frequency models are provided in Table 3. As we used multiple imputed datasets, we do not report any sample size for these models. Our original bike-share use model had 830 observations and the frequency model had 870 observations.

Table 3. Models for Bike-share Use and Frequency

Variables of the Model	**Bike-Share Use (binary)**		**Bike-share Frequency (count)**	
Variables	Mean	Est. Error	Mean	Est. Error
Intercept	-3.98	1.09	1.45	0.42
Education (base= College Education)	-0.34	0.33	-0.02	0.14
Low Income	-0.78	0.55	0.49	0.19
Middle Income	-0.22	0.30	0.37	0.13
(Base = High Income)				
Black	-0.32	0.78	-0.24	0.29
Hispanic	0.30	0.57	-0.03	0.21
White	0.48	0.47	0.01	0.16
(Base = Asian)				
Gender (Base= Man)	-0.20	0.26	-0.33	0.11
Student Status (Yes=1, No=0)	-0.60	0.52	0.28	0.14
Age (30 to 40)	-0.28	0.37	0.05	0.13
Age (40 to 50)	-0.75	0.44	0.07	0.18
Age (older than 50)	-1.48	0.40	0.32	0.19
(Base less than 30)				
Infrequent ridehail user (a few times per year)	0.77	0.43	-0.37	0.20
Moderate ridehail user (A few times per month)	1.00	0.45	-0.14	0.20
Frequent ridehail user (a few times per week or everyday)	0.28	0.71	0.05	0.24
(Base = non-user: never used or not used in the previous year)				

Variables of the Model	Bike-Share Use (binary)		Bike-share Frequency (count)	
Infrequent carshare user (a few times per year)	1.21	0.43	0.21	0.20
Moderate carshare user (A few times per month)	0.83	0.64	-0.06	0.20
Frequent carshare user (a few times per week or everyday) (Base = non-user: never used or not used in the previous year)	1.26	0.89	0.13	0.38
Infrequent bike user (a few times per year)	1.96	0.49	-0.54	0.32
Moderate bike user (A few times per month)	2.45	0.48	-0.20	0.30
Frequent bike user (a few times per week or everyday) (Base = non-user)	2.26	0.47	0.99	0.28
Infrequent transit user (one or two days in a week)	0.39	0.54	0.02	0.17
Moderate transit user (three or four days in a week)	-0.13	0.91	0.36	0.19
Frequent transit user (5 or more than 5 days in a week) (Base = non-user)	-0.17	0.68	-0.05	0.16
Zero car owner (Base = car owner)	0.61	0.59	0.36	0.17
Sd (Intercept) City	0.99	0.49	0.27	0.23

Source: Household survey and bike-share user survey

What Factors Influence Bike Share Initial Adoption and Continued Use?

Effects of Socio-Demographics

Our results show that women are less likely to initially adopt bike share, and if adopted, their frequency of use is much lower than that of men (Table 3). A gradual decline can be observed in the use of bike-share with an increase in age. Age has only a slight correlation with frequency, however: only those aged 50 years and over show a greater frequency of use compared to other age groups. Individuals with a college education are less likely to initially adopt bike share and use it less frequently compared to other groups, but the effect is uncertain. This finding is inconsistent with previous studies, suggesting it may be unique to the study area, which includes a college town with a large undergraduate student population with a very high bicycling mode share. White individuals are more likely to use the service than are people in other race groups. Asians use the service somewhat more frequently than others, while Blacks use bike-share much less frequently than others (Table 3).

Our model results outlined in Table 3 indicate that low-income respondents to the household survey (i.e., with a household income less than $50,000 or personal income less than $25,000) are less likely than respondents in other income categories to have used a bike-share service but use the service more frequently when they do use the bike-share. This same pattern is also evident for college students, although the effect is weaker and more uncertain.

These results both confirm and refute the findings of previous studies. A similar study in China of a dockless bike-share system found that it was more popular among younger, more highly educated, and median-income groups; use appeared to be independent of gender (Chen et al., 2020). However, we found a somewhat different result in the US context: low-income and male users are using the service at high frequencies than others. Rixey (2013), using socio-demographic data for the areas around bike-share stations, found that having a median income, compared to other levels, is positively associated with bike-share trips, and that being of non-white race/ethnicity is negatively associated with bike-share trips. However, we found that, if they use the bike-share service at all, people with low incomes use it more frequently than other income groups, but they are less likely to use it in the first place. This result provides an indication that initial adoption is an important barrier for low-income groups, but for those who try it, bike-share becomes a relatively frequent travel choice. One possible explanation for this result could be that members of the low-income frequent user group are more likely to have subsidized user passes. However, our data shows that the majority of low-income frequent users do not have a subsidized pass, rather they “pay as they go” like all other users (at least they self-report they do so). Thus, increasing this group in the user base will likely boost revenue for operators and address social equity.

Effect of Mode Use and Availability

Our model results outlined in Table 3 suggest that infrequent transit users are more likely to use the service than other groups are. However, moderate transit users use bike-share at higher rates than do other transit user groups. A similar pattern is seen for the ridehailing user groups with respect to using bike-share, but ridehail frequency is positively associated with bike-share frequency, suggesting a complementarity between the modes. People who have used carshare services are more likely to use bike-share than are those who have not used carshare services, but the bike-share frequency is greater for infrequent carshare users, suggesting that the modes might be a substitute for one another.

The single travel characteristic that best predicts bike-share use and frequency of use is personal bicycling. Any frequency of personal bicycling makes using bike-share much more likely, but only frequent personal bicycling is strongly related to high-frequency bike-share use.

Car ownership is negatively correlated with using the bike share system and the frequency of use. Car ownership differs significantly among the different bike-share frequency groups (Table 4). Given findings from a previous study that these individuals use bike share for a variety of purposes (Fitch et al., 2020), it can be assumed that bike share provides a strong alternative to driving for some specific trip purposes.

Segmentation of Bike-share Market

Deterministic Segmentation

We divided the bike-share users into four groups based on their use frequency in the 4 weeks prior to completing the survey and examined differences in their socio-demographic and mode use characteristics (Table 4). Here, we did not use any statistical clustering techniques, rather we divided the segments based on our understanding of the general use frequency of bike-share by an individual in a 4-week period. For defining the intervals, we used an equal interval approach. The reasons for using these intervals are: if an individual uses bike-share more than 20 times in a 4-week period, then that individual is a regular user and might use the service for commuting and non-commuting purposes (assuming they use it daily—i.e., 5 times if used unidirectionally or 10 times per week if used bidirectionally). Also, they may use it for non-commuting purposes on both weekdays and weekends. Based on these assumptions, we designated the intervals listed in Table 4.

Table 4. Socio-Demographics and Mode Use Patterns by Bike-share Use Frequency

Frequency of Bike-share Use (in 28 days)	0 and 1	2 to 20	21 to 40	More than 40
	Just Tried	Infrequent User	Frequent User	Super User
% of Individual	24%	57%	13%	6%
Education (College degree)	81%	76%	65%	70%
Student	20%	22%	32%	41%
Gender (Woman)	50%	39%	33%	22%
Low-income non-student (%)	8%	8%	11%	10%
Low income (%)	15%	18%	30%	28%
Employed	86%	89%	86%	91%
Race (White)	63%	68%	63%	66%
Bike-use (non-user)	6%	3%	2%	0%
Bike-use (Infrequent user)	24%	8%	1%	0%
Bike-use (frequent user)	39%	63%	92%	99%
Carshare Use (non-user)	85%	81%	81%	70%
Carshare Use (Infrequent user)	7%	8%	8%	20%
Carshare Use (Frequent user)	1%	2%	1%	2%
Ridehail Use (non-user)	5%	7%	14%	11%
Ridehail Use (Infrequent user)	45%	35%	29%	26%
Ridehail Use (Frequent user)	7%	11%	14%	16%
Transit Use (Non- user)	77%	72%	61%	63%
Transit Use (Infrequent user)	8%	10%	15%	12%
Transit Use (Frequent user)	10%	11%	12%	9%
Age (15 to 30)	38%	40%	39%	41%
Age (Older than 50)	14%	10%	15%	17%
Zero car individual	8%	12%	22%	27%

Source: Bike-share user survey

Table 4 shows that the super user group is distinctly different from the other groups with respect to certain characteristics. This group is predominantly made up of men who are car-less, have lower-incomes, are heavy transit-users, and use a variety of other modes such as carshare, ridehail, and personal bike. This group is by far the most multimodal. As a large portion of the low-income individuals may be students, we also separate students from the low-income group to produce another low-income group without students. This also shows that frequent and super users consist of a greater proportion of low-income non-student users.

The group of those who have just tried the service (using it 0 or 1 times in the last 28 days) is mostly made up of car owners who use transit very little, are highly educated, have high incomes, and have the lowest frequency of using a personal bike. Very few members of this group are students. This is the least multimodal group compared to others.

The infrequent user group is the largest group of users and is mostly made up of male users who use personal bikes, carshare, ridehail, and transit at somewhat greater rates compared to the "just tried" group. The frequent user group consists of mostly male users with a high percentage of students and with a high average bike use, transit use, and zero car ownership rate compared to the preceding groups.

Psychometric Segmentation

Attitudes Toward Travel Modes

For the analysis of the influence of latent attitudes on bike-share use, we segmented bike-share users into groups based on their mode-related attitudes (e.g., pro-bike, pro-car, etc.), attitudes regarding the social environment for bicycling, and concern about bicycling. We extracted three segments based on these individual attitudes. We found minor differences in the use of the bike share among the three segments. The characteristics of the segments, also called clusters, are shown in Figure 2. The radar plots illustrate the characteristics of the different clusters with respect to different variables, with the upper plot showing results for socio-demographic and travel-behavior variables and the lower plot showing results for attitudes. These plots show the relative position of each cluster with respect to each variable. For a given variable, if the color of a cluster extends towards the border of the radar, that indicates that the cluster has the highest value for that variable, and if the color of a cluster is not visible for a variable, that indicates that the cluster has the lowest value for that variable.

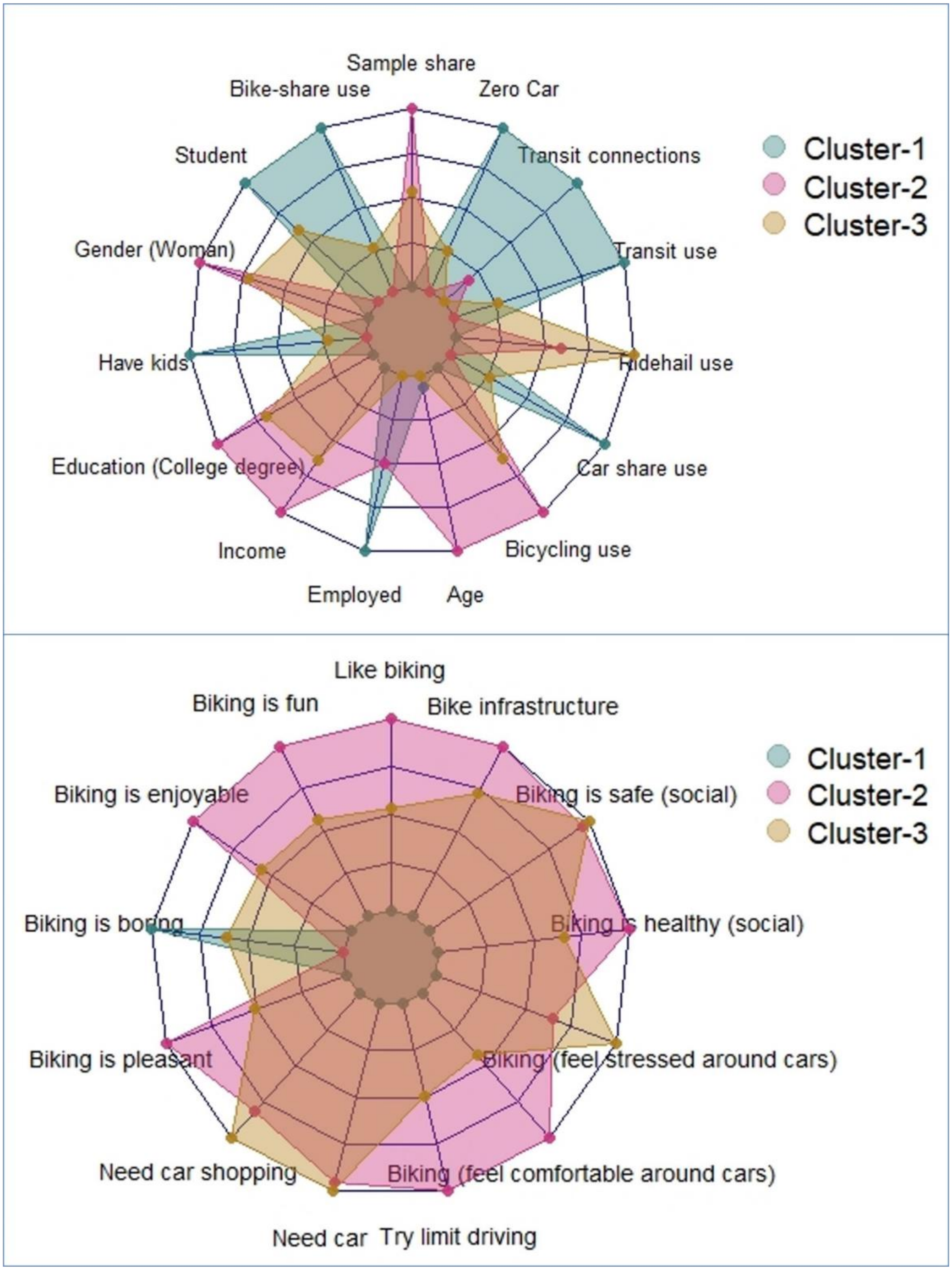

Figure 2. Market segments based on bicycling, car, and social environment around bicycling-related attitudes (Source: Bike-share user survey)

Cluster 2 is the largest cluster (52% of the sample) but has the lowest use of the bike-share service. In this cluster, compared to the other two clusters, the average scores for positive attitudes towards bicycling are highest, as is the use of their personal bikes. This cluster has the lowest score for "biking is boring" and a moderate score for feeling stressed when bicycling around cars. We call this the "pro-bike" cluster. This cluster mainly consists of college-educated and middle- and high-income individuals. Although they are pro-bike, they express a high need for a car, but they say they try to limit their driving. This segment has a greater percentage of car ownership than the others. Their lower use of the bike-share service is likely due to fulfillment of their travel-related activities by driving and by personal bicycles. The potential for increasing bike-share use among this group may not be high.

Cluster 1 is the smallest among the three clusters (23% of the sample). Members of this cluster use bike-share more frequently than other clusters. However, their scores for positive bike attitudes and perceptions of the social environment for bicycling are the lowest among the three clusters. We call this cluster the "car alternatives" cluster. The members of this cluster, compared to the other clusters, have lower incomes on average and are more likely to be male, be a student, be employed, and have children. They are more likely to live in zero-car households, say they do not need a car, and do not say that they try to limit their driving. The use of personal bikes is lowest in this group compared to the others, but transit use is higher, as is the use of bike share to connect to transit. The use of car-share is also considerably higher for this group. This group appears to depend on modes other than driving their own cars, and their frequent use of bike-share suggests that the system has been important in expanding the options available to them, even if they do not necessarily enjoy bicycling. Expanding this market segment could help to achieve the goals of increasing the demand for bike-share and contributing to a more equitable transportation system.

Cluster 3, the second-largest cluster (34% of the sample), has a low frequency of bike-share use. Individuals in this cluster have a moderately positive attitude towards bicycling. Their feelings about bicycling seem somewhat conflicted: they have a high score on the perception that bicycling is safe but the highest score of the three clusters on feeling stressed when bicycling around cars. They bicycle a moderate amount compared to the other two clusters. On the other hand, they are more likely than the "car alternatives" cluster to own a car and are the most likely of the clusters to say that they need a car while they are not likely to say that they limit their driving. We thus call this cluster the "driving oriented" cluster. They use ride-hailing more than other clusters (but not car-sharing) and use transit more than the "pro-bike" cluster but far less than the "driving alternatives" cluster. Although driving-oriented, this cluster might be open to increasing their use of the bike-share service under the right conditions.

Overall, the above analyses indicate that a positive attitude towards bicycling has a strong association with personal bike use but a weak association with bike-share use. Thus, general attitudes toward bicycling may not play a large role in bike-share use, at least in the early days of the service. Rather, frequent use seems to be driven by travel needs coupled with limited access to a car.

Perceptions toward the bike-share service

We extracted three different clusters based on the responses to the bike-share-related perception statements. The socio-demographic and mode use pattern analysis for the clusters is shown in the upper plot in Figure 3 (the same variables are shown in the upper plot in Figure 2). The lower plot shows the differences in clusters with respect to their perceptions of the bike-share service.

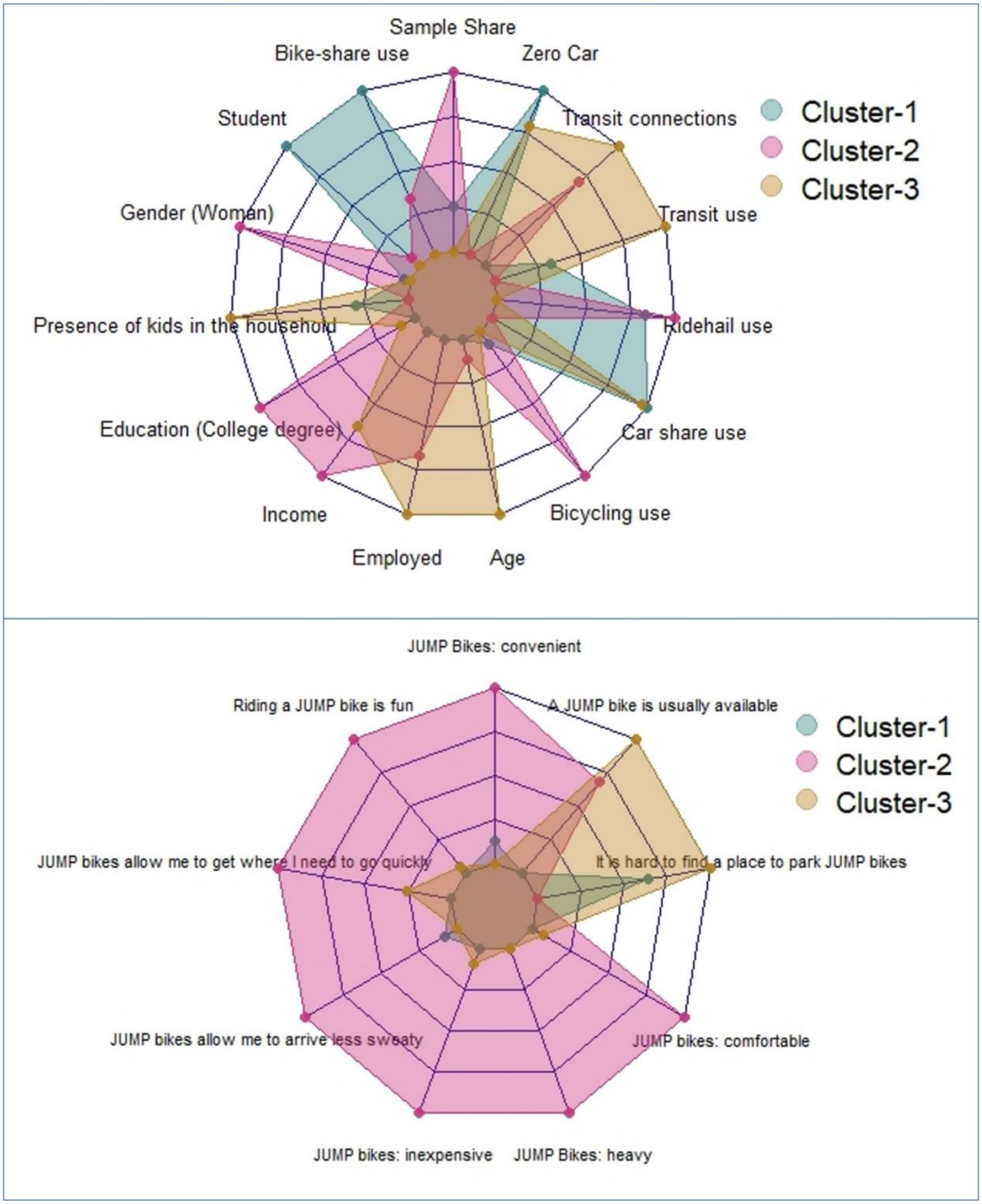

Figure 3. Market segments based on perception towards bike-share of users (Source: Bike-share user survey)

Cluster 1 is the second-largest cluster (25% of the sample). This cluster has a very high rate of bike-share use. However, individuals in this cluster have the least favorable attitude towards the bike-share service. Also, the high score on the *hard-to-find parking* (for the bike) and low score on *bike usually available* perception statements indicate that frequent users of bike-share may be more likely than infrequent users to experience bike unavailability and parking difficulty. We call this cluster the "disgruntled users" cluster. The negative association between perceptions of bike-share and bike-share use indicates that perceptions of the service may have little influence on the use of the service. Rather, the unavailability of cars and lower-income status is probably the main reason why this segment uses the bike-share service. Car ownership is the lowest in this segment, personal bicycling use is low, and use of car-share service is high.

Cluster 2 is the largest cluster (62% of the sample). This cluster has the highest scores for perception-related aspects of the bike-share service. However, their favorable views of the service do not translate into greater use: members of this segment use the service at a moderate rate. We call this the "satisfied user" cluster. In addition to being moderate users of the bike-share service, this cluster uses personal bikes more frequently than the other two clusters and have a high car ownership rate. This user segment consists of a higher proportion of college-educated and middle- and high-income individuals. Their use pattern and other characteristics suggest that they are not likely to be an important segment for growing demand.

Cluster 3 is the smallest (13% of the sample) among the three clusters. Although their socio-demographics are similar to those of Cluster 1, this cluster has the lowest rate of bike-share use and very low scores in most of the perception-related aspects of the bike-share. This group mostly consists of male users and has a very high rate of zero-car owners. They use personal bikes at a very low rate but use transit and carshare at a very high rate compared to others. Their frequent use of transit suggests that a portion of their travel needs is fulfilled by transit and that may be why they use bike-share less frequently, even if they do not own a car. We call this the "transit user" cluster. When they do use bike share, they often do so to connect to transit. The members of this group can be a potential market for bike-share due to their lower car availability; however, targeting this group should involve providing them options that are integrated with transit passes.

Overall, these analyses suggest that more positive perceptions of the bike-share service do not necessarily translate into greater use. They also show that apart from low-income and zero-car households, another potential market can be transit users. To attract this market, operators should consider offering bike-share payment packages integrated with transit.

Market segments based on travel-related concerns

We extracted three clusters based on travel-related concerns. The differences between these clusters are plotted in Figure 4 in a similar manner to the two previous analyses.

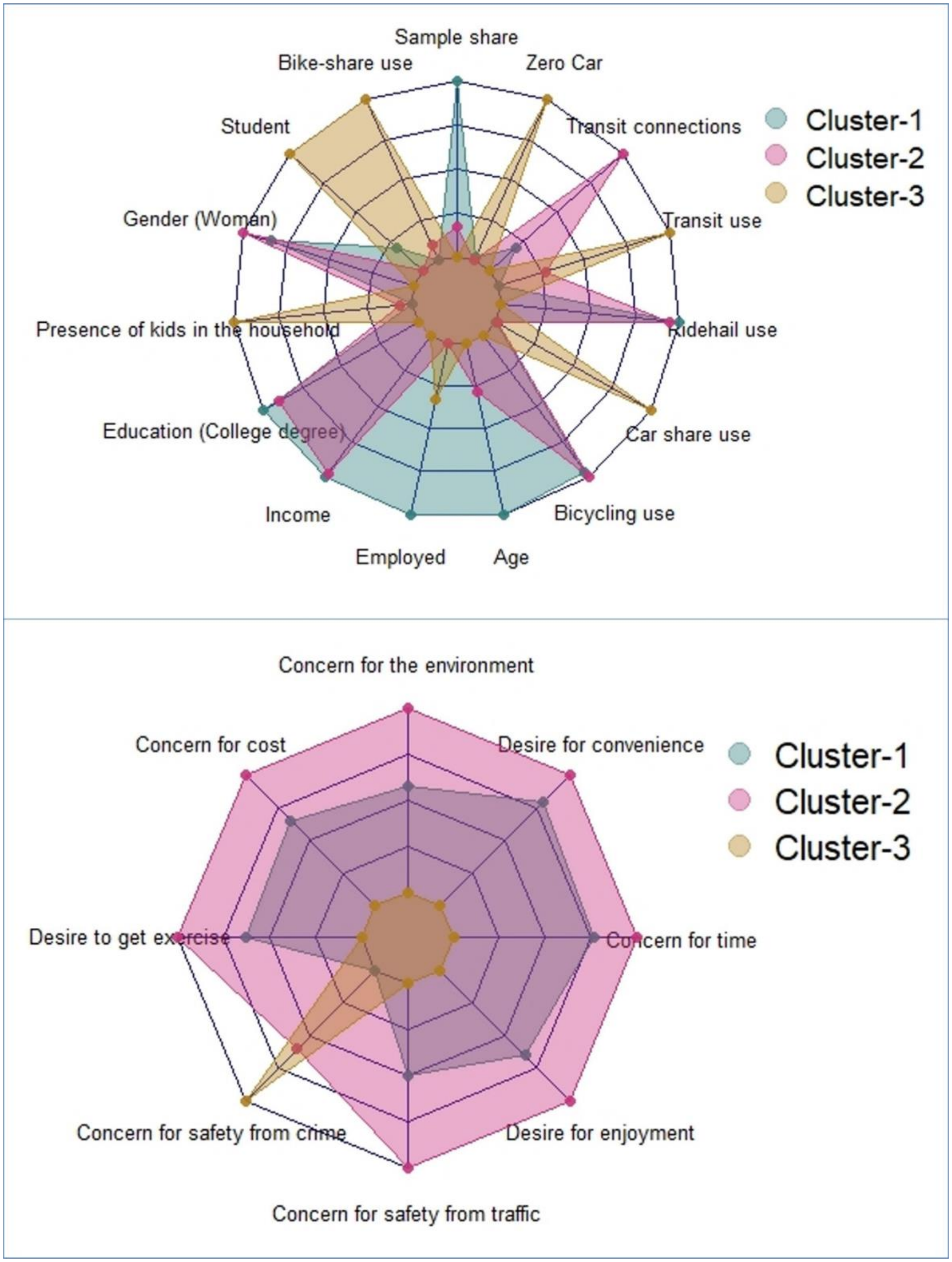

Figure 4. Market segments based on different travel and environment-related concerns of users (Source: Bike-share user survey)

Cluster 3 is roughly similar in size to the other two clusters (31% of the sample). Individuals in this cluster, as compared to those in the other two clusters, have less concern for the environment, travel cost, traffic safety, travel time, and travel convenience, on average. However, they express greater concern about safety from crime when making decisions regarding travel. This concern for safety from crime while traveling is possibly aligned with the fact that a larger portion of this group has children compared to other clusters. We call this the "safety concerned" cluster. Its members tend to use bike-share at a higher rate compared to others. However, this group has a very low personal bicycling rate. Their frequent use of transit and carshare is not likely due to their concern about the environment but rather to their limited choices stemming from low income and car ownership levels. Unlike the "transit user" cluster (see previous analysis), this group uses both transit and bike-share frequently and does not have a high score for using bike-share to connect to transit. Thus, promotional efforts that integrate bike-share and transit packages may not work for this group.

Cluster 2 consists of individuals who have higher concerns for the environment, travel cost, travel safety, travel enjoyment, travel time, and travel convenience. We call this the "widely concerned" cluster. This group is similar to Cluster 1 with respect to socio-demographics as well as bike-share use. Cluster 1 consists of frequent bikers who are mostly upper-middle-income. However, this group uses the bike-share service at a moderate rate and bikes at a very high rate. The members of this cluster have more moderate concerns than the members of the "widely concerned" cluster. We call this the "moderately concerned" cluster.

Overall, the above analysis indicates that the use of bike-share is not generally driven by different environmental and travel-related concerns but rather by the availability of other modes. Findings from this cluster analysis also validate the findings from the previous cluster analysis where a large segment of those not bicycling or infrequently bicycling was found to be using the bike-share service frequently. This suggests that bike-share has the potential to attract non-bikers into bicycling and that the bike-share operators can reach out to a larger segment of the population and do not need to limit outreach to existing bicyclists.

Behavioral Segmentation

Market segments based on the bike-share use purpose

We classified survey respondents into four clusters based on their bike-share use for commuting and different non-commuting purposes. The characteristics of this cluster are shown in Figure 5. Compared to the other segmentation methods described above (i.e., segments based on attitudes, perceptions, and travel-related concerns), this behavioral segmentation produces a better result in terms of differentiating bike-share users based on their use frequency.

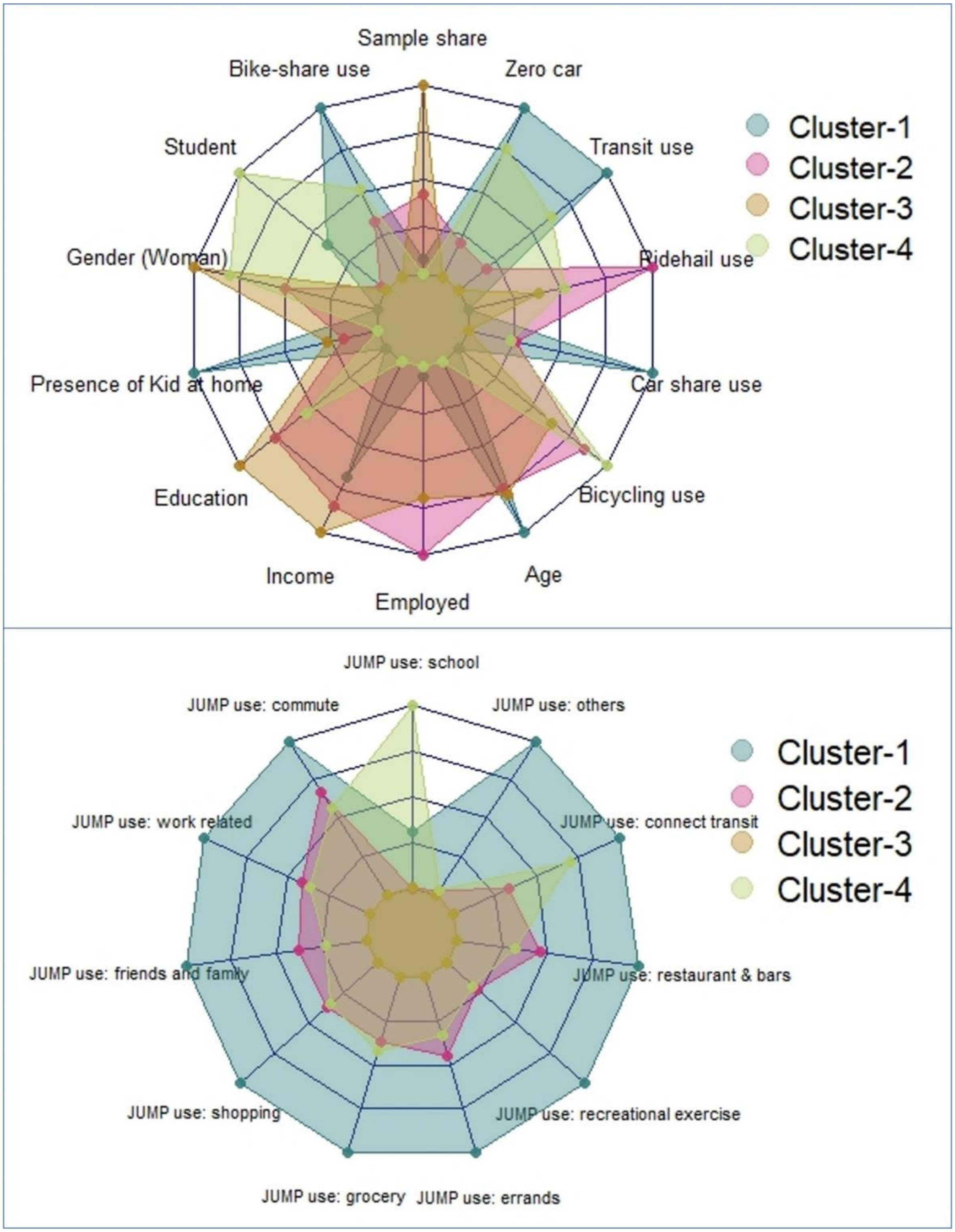

Figure 5. Market segments based on the use of bike-share for commuting and different non-commuting purposes (Source: Bike-share user survey)

Cluster 3 is the largest group of users (52% of the sample). They have the lowest score in most of the use purpose categories and, consequently, the lowest bike-share use rate. We call this the “dabblers” cluster. This cluster has the lowest proportion of the student population and mostly consists of middle-income individuals. Their transit use rate is the lowest among others.

Cluster 4 is the smallest group of users (9.2% of the sample). They use bike-share at a very high rate. Their frequency of using bike-share for most purposes is moderately high, but their frequency of use for going to school is greater than other clusters. This group mainly consists of students, so we call this the “school” cluster. This group also uses personal bikes and ridehail at much greater rates compared to others, consistent with the fact that more than half of this group does not own cars. Individuals with similar characteristics to this cluster who are non-users of the bike-share are a potential market for the bike-share operator.

Cluster 1 uses bike-share at the highest rate. This group has the highest average frequency in most of the trip purposes, indicating that its members use bike-share for a variety of purposes. We call this the “multi-purpose” cluster. However, their personal bike-use frequency is much lower compared to others. Approximately half of the members of this group are students. This group also consists of lower-income, car-less individuals who use transit and carshare frequently. Although this group has very low car ownership, the use of ridehailing by this group is still the lowest among the four groups, a result that may be due to the high cost of ridehailing. This group can be an appropriate market for bike-share operators as they are multimodal but not bike users. Their infrequent use of personal bikes also implies that bike-share was important in causing this group to ride bikes.

Cluster 2 is the second largest group (27% of the sample). They use bike share moderately frequently. Their use of bike-share for commuting, going to restaurants and bars, and doing errands is greater than for other groups. We call this the “utilitarian” cluster. The use of bike share for other purposes is limited for this group. This group mainly consists of male users and middle-income individuals who also frequently use their personal bikes. As more than two-thirds of the members of this group have cars, it is not surprising that their use of transit and carshare is limited. This group can be a good target for marketing bike-share for specific trip purposes and boosting the use of the bike share for those purposes at different times of the day. Targeting this segment may require bike-share operators to think about the location of specific kinds of destinations (e.g., restaurants, bars, and errands) associated with specific trip purposes and deploy bikes to these areas accordingly.

Market segments based on commute modality classes

Our final analysis examined market segments by modality classes for commuting, where modality classes are based on what mode or modes individuals regularly use for commuting purposes. We extracted three clusters that represent distinct modality classes. The characteristics of the different modality classes are shown in Figure 6 in a format similar to the previous market segmentation analyses.

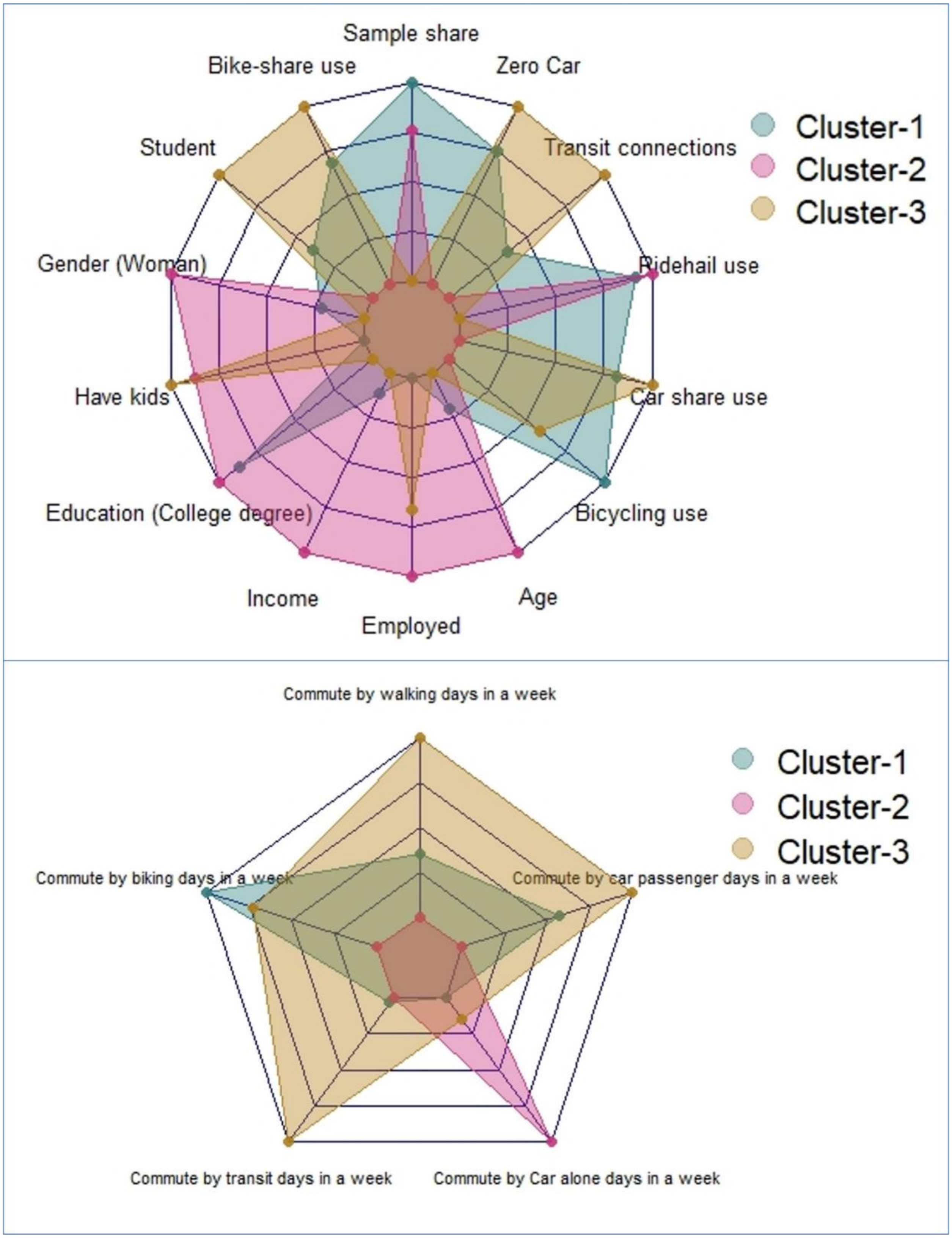

Figure 6. Market segments based on modality styles (Source: Bike-share user survey)

Cluster 3 is the smallest cluster (16% of the sample) and has a very high rate of bike-share use. This group also has very high rates of walking, biking, and transit use and a very low rate of car use for commuting. We call this the “super multimodal” cluster. This cluster also uses bike-share services to connect to transit at a very high rate. This cluster has a very high share of members who do not own cars. Non-users of bike-share of similar characteristics are a potential target for boosting bike-share use.

Cluster 2 is the second-largest cluster (38% of the sample) and mainly uses cars for commuting. Although this group has a moderate rate of personal bike use, they use bike-share at a considerably lower rate than the other clusters. We call this the “driving” cluster. Their personal bike use is limited to non-commuting trips, and the zero-car ownership rate of this cluster is exceptionally low (1%). Individuals with characteristics similar to this segment are presumed to have the lowest future potential to increase their bike-share use.

Cluster 1 is the largest cluster (45% of the sample), and the majority of the members use bikes (either bike-share and/or personal bikes) and/or walk for commuting trips. Along with high personal bike use, this group also uses the bike-share service at a higher-than-average rate. We call this the “active travel” cluster. Their transit use rate is very low, indicating they mainly use bikes for their entire commute. Car-less individuals make up a considerable portion of this group. Individuals with similar characteristics who are not already using bike-share are a promising potential market for bike-share as a commute mode.

Bike-share Related Approaches for Target Markets

Our statistical modeling and market segment analyses indicate that bike-share use may not be linearly related to some socio-demographics and mode user groups. Several other attitudes, perceptions, and modality styles influence bike-share use. Some socio-demographic groups are using the service with a very high frequency compared to the mean model predictions. This phenomenon is clearer from the detailed market segmentation analyses. Market segmentation results suggest that the most important socio-demographic characteristics to target for increasing the use of the bike share are low income and student status. The most important travel-related variables are ridehail use, transit use, and car ownership. Targeting the people in these groups who are not yet using bike-share can bring newer users who are likely to use the service frequently and boost ridership.

We did not find a strong association between positive bike-related attitudes and bike-share use (i.e., “pro-bike” cluster), indicating that bike-share use may be mostly driven by the availability of other modes of transport. Also, we found that frequent users tend to hold a lower perception regarding the bike-share service. Although this seems counter-intuitive, it suggests that the causality goes the other way – using the bike-share service affects perceptions of the service, rather than perceptions of the service affecting use. The frequent users know more about what the service is like, and they may have higher expectations than users who do not use bike-share frequently. This can be helpful for bike-share operators as they aim to improve the service experience for their users. Analysis of commute modality style revealed an “active travel” cluster and a “super multimodal” cluster. As both of these groups use the services regularly, cities and operators need to devise different types of approaches for each group.

In general, all the results show that those people who use bike-share more frequently tend to live in a zero-car household and tend to be students. These findings imply that bike-share operators can market the product to the members of these groups that are not already using it and target them. Those users who only infrequently use bike-share are often auto users, have high incomes, and are frequent bicyclists (using personal bikes).

Importantly, frequent bicycle users do not always necessarily use the bike-share service frequently as the modeling result suggests. In fact, there is a market segment named the “safety concerned” cluster that infrequently rides a personal bike but uses the bike-share with high frequency. Based on bike-share use purpose analysis, we found a “multi-purpose” cluster who use bike-share for a variety of purposes, however, they use personal bicycles at a very low rate. This is an important market segment that may not be fond of personal bike use but interested in electric shared bike use; thus, it has the potential to boost electric shared bike ridership. This also indicates the introduction of bike-share has attracted a segment of the population that is using shared bicycles for commute and different types of non-commute-related trips. Further exploration of the market segment can discern what factors influence them to use the shared electric bikes (e.g., the electric feature of the shared bike, concern regarding personal bike theft, branding aspects of the shared electric bikes, etc.) and help to target similar character individuals who are not yet using bike-share.

Because of the complexity of these results, we synthesized the results by outlining approaches for getting new users who have the potential to use the service frequently as well as approaches for increasing use among existing users.

Approach 1: Increase Low-income Users

Individuals with low incomes are less likely to have used bike-share but have a much greater frequency of use if they do use it. A higher number of low-income bike-share users will further boost the use of the service. One reason for the lower rate of use may be the unavailability of the service in low-income areas. Pricing and payment systems may be another factor, along with insufficient marketing efforts targeting low-income individuals. Policies that make the service more available and affordable to low-income individuals would increase equity as well as demand.

Approach 2: Increase Student Bike-share Users

Like low-income individuals, students are less likely to use the service, but if they use the service, they do so much more frequently than non-students. The high frequency of use may be due to the provision of student-friendly rates and subscription offers (Kaeppeli, 2019). Devising appropriate policies that target student users could get more students in the user base. Providing low-fare service to this group is important as they not only use the service frequently but also can be long-term future users of both bike-share and personal bikes by developing a habit of biking.

Approach 3: Increase Transit Users

From our market segment analysis, we found two types of transit user segments. One group uses transit and bike-share frequently (i.e., "car alternatives" cluster) and another group uses transit frequently and uses bike-share infrequently (i.e., "transit user" cluster). Strategies should be devised to attract these two different segments. For instance, frequent transit users are a promising group to target as a portion of them use the bike-share service for first and last-mile connections to transit. Although currently small in proportion, the percentage of these types of travelers can be increased through appropriate strategies, developed in collaboration with transit agencies, such as integrated trip payment and discounts, placing bike share stations near transit stops, and developing subscription options for frequent transit users along with their transit pass (Mass Transit, 2019). Many transit operators are already considering the potential of the bike-share to connect to transit in their transit plans (Mohiuddin, 2021). If the bike-share operators can attract more transit users in the bike-share user base, we can observe a complementary effect of the bike-share on transit.

Approach 4: Increase Zero Car Owner Users

Individuals from zero-car households make up a large segment of bike-share users. This group generally uses transit (Tomer, 2010), ridehailing (Brown, 2020), personal bicycling, and car sharing (Martin et al., 2010) to meet their travel needs. However, the use frequency of these different multimodal options differs for many other factors. A portion of this carless group mainly uses transit and carshare (i.e., "transit user" cluster) while others mainly use ridehail and personal bikes (i.e., "school" cluster). Another portion of this group is largely using active modes (i.e., "active travel" cluster). Strategies for attracting those different segments should be different. Some of the strategies for targeting different multimodal user groups can also work with the strategies for targeting low-income students, as a considerable portion of transit users and zero-car households are low-income (Clark, 2017; Tomer, 2010). Integrating different mode options in a unified mobility market through the "mobility as a service" (MaaS) concept could attract these individuals to bike-share, helping to boost the overall use of the service. In the "mobility as a service" concept, a single smart-phone app (or possibly payment card) can be used to access multiple mobility options, with the potential for differently discounted trips via ridehailing, transit, bike-share, scooter-share, taxi, carshare, etc.

Approach 5: Increase Both Frequent Ridehailing Users and Non-ridehailing Users

Frequent ridehail users and non-users of ridehail use bike-share services at high frequencies. Ridehail and bike-share companies can collaborate to encourage multimodal users towards more frequent bike-share as well as ridehail use.

Approach 6: Explore Bike-Share Barriers Specific to Women

One of the glaring findings from the above results is that women are less likely than men to adopt and use the bike-share service. This is consistent with the previous studies on bicycling that show that women are less likely than men to bicycle. However, further research is needed to understand if there are barriers for bike-share use that are specific to women beyond the general bike gender gap. Perhaps bike-share services have the potential to help reduce some gender barriers. For example, the need to transport children is an often cited obstacle to bicycle use by women (Garrard et al., 2012a), bike-share services might provide more e-bikes or cargo bicycles. Of course, many barriers cannot be reduced from bike-share alone such as the need for increased traffic safety and personal security.

Approach 7: Increase the Number of Shared Bikes

The Sacramento area is known for the highest per day per bike use of the bike-share system (CAPO VELO, 2019; Schmitt, 2018). As the frequent users report dissatisfaction regarding the unavailability of the service, deployment of more bikes can improve the service quality for existing users as well as attract new users. This approach is important, especially if the other strategies are used to increase the number of users. This will increase the likelihood that current users are satisfied so that they continue to use the service or even increase their frequency of use. Increasing the number of bikes in total also allows easier deployment in neighborhoods where a higher proportion of low-income, transit users, bike users for commuting, and zero-car households reside. In this way, this approach can mutually work with other approaches by making the shared bikes available to a certain segment of the population who have unmet transportation needs.

Policy Implications and Conclusions

Bike-share services are growing across cities in the US and have served as a substitute for less sustainable travel modes (Fukushige et al., 2021). Many cities have goals beyond mode shift, including social equity and mobility justice. For cities to achieve environmental and social goals, it is important to know what factors influence initial bike-share adoption and continued use of the service. In this study, we conducted statistical behavioral modeling and market segmentation analysis to identify the factors influencing adoption and continued use as well as the attitudes, preferences, and modality styles of the different bike-share user groups. The results from this study can help cities and bike-share operators make these services more accessible and practical for various groups, including those who are already using and those who have not yet used bike-share.

Addressing equity is a major concern when planning and operating bike-share (Bhuyan et al., 2019; Duran-Rodas et al., 2021; Grasso et al., 2020; Howland et al., 2017). Although the dockless bike-share system has considerably reduced the access barriers posed by the station-based systems (Qian et al., 2020b), our analyses show there is still a significant difference among different socio-demographic and mode-user groups in terms of using the service. Our data shows that only 8% of the low-income non-students are using the service. Although our sample of bike-share users may not be representative of the bike-share user population, it still indicates a low adoption of bike-share by the low-income segment. While some evidence suggests bike-share has been more focused on wealthier neighborhoods to attract demand (Duran-Rodas et al., 2021), we show that addressing equity may not have to correlate with lower demand and lower utilization of bike fleets. Instead, we found that certain demographics such as high-income car-user groups use the service at a very low frequency. This group may have specific travel needs that may not be serviceable by bike-share. As the operators have a fixed number of devices, deploying a large proportion of bikes in areas of high income and high car ownership may not align with the equity goals of the bike-share or even lead to higher use-rates and revenues.

Our survey data suggest that low-income carless residents can use the service frequently and for a variety of purposes if the service is designed for them. The results also suggest that these frequent user groups are not subsidized users of daily or monthly passes; rather they pay per trip basis and pay at the same rate as the other middle-and high-income users. Increasing the proportion of these types of users in the bike-share user base will likely increase the revenue of the operators. Thus, operators can consider deploying bikes in block groups that have a higher proportion of low-income and zero-car households. Marketing bike-share services to those groups can be useful for increasing new user recruitment. These initiatives can assist in achieving social equity in the bike-share service operation and boost ridership.

Future research should explore the more direct link between policies and both demand and equity outcomes. This will require evaluations of actual real-world policies through surveys and data collection before and after policy implementation. In the wake of COVID-19, when both bike-share and scooter share was abandoned in many cities (Bureau of Transportation Statistics, 2021), cities will have the opportunity to re-envision bike-share as a service that not only provides a sustainable travel option but also a service that is designed with policies to grow bike-share demand over time and increase transportation equity.

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Data Summary

Products of Research

This study used data collected from a two-wave repeat cross-sectional household survey and a two-wave intercept bike-share user survey. A before-and-after survey was designed to measure the effect of the bike-share service on levels of bicycling, transit use, and vehicle miles of travel as well as attitudes towards bicycling. Before the introduction of the bike-share, in the spring of 2016, a household survey was conducted in the Sacramento region. Then after the introduction of bike-share, in the spring of 2019, another household survey was conducted in the Sacramento region. The method of survey sample recruitment was repeat cross-sectional address-based stratified random sampling. After the introduction of bike-share, in the fall of 2018, a bike-share user survey was conducted. In the spring of 2019, another bike-share user survey was conducted. In the bike-share user survey, sample recruitment was done by intercepting the bike-share users with fliers. Additionally, a bike-share user panel survey was conducted (re-recruitment of prior participants). In each of the surveys, respondents were asked about their access to and use of different transportation modes, attitudes towards bicycling and other aspects of transportation, experience with bike-share services in other regions, and socio-demographic characteristics including income and race/ethnicity. All surveys were done through an online web survey system (i.e., Qualtrics).

Data Format and Content

The dataset contains six files. These files describe the travel behavior and travel mode-related attitudes of residents and bike-share users in the greater Sacramento region. The data includes the socio-demographics, travel and mode-related attitudes, and mode use pattern of both users and non-users of the bike-share service. For instance, "Jump_User_Survey.csv" file contains the two waves of bike-share user survey data of different variables and the "Jump_User_Survey_Metadata.csv" provides a description of each variable. Missing values are present in many variables when survey participants chose not to answer a question (indicated by NA or blanks). Similarly, the other four files contain two household survey data and their associated metadata.

Data Access and Sharing

Anyone can access the project data from https://doi.org/10.25338/B8BK9V.

Reuse and Redistribution

 The user of the data is encouraged to appropriately cite the data using the following suggested citation:

> Fitch, Dillon; Handy, Susan (2022), Sacramento bike-share surveys, Dryad, Dataset, https://doi.org/10.25338/B8BK9V