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Examining market segmentation to increase bike-share use and enhance equity: The case of the greater Sacramento region

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ABSTRACT

As bike-share systems proliferate across the US, a deeper understanding of current bike-share users could enable an expansion of these services and their benefits to a larger population. To grow bike-share demand sustainably and equitably, cities must understand how different segments of the population use this service. Understanding the different segments within a market enable operators to develop strategies that are tailored toward the needs of each segment. This study uses data from bike-share user surveys in the Sacramento region to perform market segmentation based on perceptions of the bike-share service, mode use patterns, and bike-share use. We focus on the market segments with more limited means of transportation: low-income individuals, zero-car households, students, and transit and car-share users. The results show that individuals with low incomes, those without cars, and students use the service frequently for commuting and a variety of non-commuting purposes. Bike-share is generally adopted by all mode user groups but is used at a higher rate by the super multimodal and active multimodal groups. The occasional users of the bike-share service are mainly those with higher incomes and individuals who have access to a personal car. The segments consisting of non- and infrequent-personal bike users use the bike-share service at a greater rate for different purposes than regular bicyclists, suggesting that bike-share may act as a lever for increasing bike travel for some users. Results from data mining suggest that bike-share operators should target low-income and zero-car owners for new recruitment as these groups are more likely to use bike-share frequently. The results provide insights that may be helpful to cities as they consider strategies to increase bike-share demand in a way that enhances social equity.

1. Introduction

Many cities around the world have embraced bike-share systems in the last decade as an important mobility option that can help cities to achieve sustainability goals (Fishman et al., 2013). These systems have attracted substantial ridership, even in the U.S. (National Association of City Transportation Officials, 2020). Evidence shows that micromobility (i.e., bike-share and scooter-share) services often substitute for car use (Fukushige et al., 2021; Fuller et al., 2013; Hsu et al., 2018; Wang et al., 2022). Bike-share systems can also play a role in supporting transit by providing an option for the first or last leg of the transit trip (Fitch-Polse et al., 2023; Mohiuddin, 2021; Mohiuddin et al., 2023b; Shaheen and Chan, 2016; Fukushige et al., 2022) thereby serving as a solution for the first and last mile problem in urban contexts (Oeschger et al., 2020). In this way, bike-share services have the potential to enhance transportation equity (Mohiuddin et al., 2023a). Studies show that bike-share services may influence individuals' travel behavior and attitude toward cycling (Fitch et al., 2020, 2021; Shaheen et al., 2013). The service can be used by different groups of travelers with various transportation needs.

To grow bike-share demand sustainably, cities must understand how different segments of the population use this service. Marketing research concepts are useful in this regard. 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). A market segment is a collection of individuals who are behaviorally similar from the perspective of the researcher. Many North American studies have explored market segments for bicycle commuting, but few have examined market segments among bike-share users. Several studies have reported that bike-share users are mainly middle- and high-income and predominantly white (Oates et al., 2017a; S. A. Shaheen et al., 2014; Wachsmuth et al., 2019). However, along

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with socio-demographics, it is important to understand how perceptions of the bike-share service and the use of other modes of travel differ across user segments. Detailed bike-share market analysis can be used to tailor urban transport policies as well as target customer segments to boost demand (Morton, 2018). For example, cities can examine how individuals with fewer transportation options are using bike-share and formulate policies to increase the availability and use of the service to those segments to address social equity.

In this study, we segment the bike-share market using a statistical clustering method, and we explore the characteristics of frequent and "super users" of bike-share using a data mining approach. Data come from surveys of users of the electric bike-share system in the greater Sacramento area and include measures of user perceptions, purpose of use, and mode use patterns for commuting. We focus on examining the market segments with reference to selected socio-demographic and mode user groups who have more limited means of transportation: low-income status, zero-car households, students, and transit and car-share users. A bike-share system can improve social equity if the service is available to the groups who struggle to afford transportation, who cannot own or use a personal car, and who are likely to have fewer available transportation options. As these groups can especially benefit from the enhanced accessibility to opportunities the service provides, achieving a disproportionately high share of transport disadvantaged groups in the user base is an indicator of the contribution of bike share service to social equity. We investigate the relationship between market segments and bike-share ridership and its use for different purposes with reference to the above-mentioned socio-demographic and mode user groups to address the following questions:

Q1. What market segments exist among bike-share users?

Q2. How does the use of the bike-share system vary across market segments?

Q3. How can bike-share demand be grown while addressing social equity?

2. Literature review

Although there is a dearth of research on bike-share market segments, much research is available on bicycling market segments, and these studies may be useful in the development of an approach to segmenting the bike-share market. Studies have used both socio-demographics variables alone or in combination with travel behavior and use frequency for different purposes variables to segment the bicycling market using a variety of methods (Bergström and Magnusson, 2003; Deakin, 1985). However, these segmentation analyses do not account for the fact that individuals with similar socioeconomic characteristics can make different transportation choices (Li et al., 2013), an omission that can oversimplify the market segments (Anable, 2005). Other evidence suggests that apart from socio-demographics, attitudes towards bicycling, safety, and convenience influence bicycle use (Dill and Voros, 2007; Noland and Kunreuther, 1995; Stinson et al., 2005; Mohiuddin et al., 2022a,b). A study by Heinen et al. (2011) reported that attitudes had a strong impact on the choice of bicycle for commuting (Heinen et al., 2011). The same study also shows that socio-demographic characteristics explain a limited portion of a traveler's attitude.

Studies of bike-share users are another starting point. These studies have mainly explored the socio-demographics of the users. One study compared bike-share users with regular cyclists and found that users are more likely to be female, younger, have lower incomes, have fewer cars and fewer bicycles, and are more likely to cycle for utilitarian purposes (Buck et al., 2013). Another study using user and non-user data from the Vancouver public bicycle share system explored the current and potential market for the service with respect to socio-demographics, travel behavior, motivation, and barriers to using the service (Hosford et al., 2018). Apart from socio-demographic characteristics, individuals can be heterogenous in their patterns of using the bike-share service. Research shows that heterogeneity may arise not only based on the observed characteristics of the individual (e.g., socio-demographics) 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. Understanding those heterogeneities may be helpful in developing targeted programs for addressing equity and enhancing service use. One study using London bike-share user data segmented the bike-share users using the perceived quality of the service, user satisfaction, and behavioral intention along with socio-demographics (Morton, 2018). Those findings suggest that it is important to include both socio-demographics as well as individuals' perceptions to identify market segments and characterize different user groups.

As bike-share services proliferate in cities across the world, understanding the demand for the services as well as their contribution to enhancing transportation equity is important. Recent studies have provided some insights on both of these aspects but leave open the question of how both bike-share demand and equity can be achieved together. Duran-Rodas et al. (2021) explored different scenarios for balancing bike-share ridership and equity using station-level bike-share ridership and census-level socio-demographic data from Munich, Germany. The authors found that addressing equity scenarios results in placing bike-share in places that serve disadvantaged areas while focusing on ridership scenarios results in the locating of bike-share stations near rich neighborhoods. The relationship between bike-share demand and neighborhood socio-demographics varies widely. For example, Duran-Rodas et al. (2020) found that areas with a higher proportion of disadvantaged residents have lower bike-share ridership. Alternatively, Oates et al. (2017b), using bike-share data from Birmingham, Alabama, and Rixey(2013), using bike-share data from Washington DC, Denver, and Minnesota, found the opposite. Although the study area context may explain the differences, the use of aggregate census-level socio-demographics and station-level ridership data may also mask the underlying socio-demographics of bike-share users. These nuances suggest that rather than focusing on aggregate-level socio-demographics of areas where bike-share users reside, it is important to consider the individual-level socio-demographics and behavior of users. For instance, a study by Winters et al. (2019) using individual-level bike-share user data from Vancouver found that "super users" of bike-share are more likely to be young, male individuals with incomes less than $75,000 and have fewer transportation options. It is also important to understand the bike-share use of underrepresented demographic groups as indicators of the broader supportive contexts for bike-share use since studies show that higher income and white individuals are overrepresented in the bike-share user base (McNeil et al., 2018; S. Shaheen et al., 2014). Segmenting bike-share users and analyzing the behaviors of individuals in the different segments can complement traditional ridership and equity analyses.

Researchers have used several methods for performing different types of market segmentation. Clustering is the most widely used method for market segmentation in consumer studies (Dolničar, 2003). The clustering method attempts to 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; 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).

Several recent studies have used the clustering method for segmenting individuals for analyzing emerging mobility services such as electric vehicles (EVs), ridehailing, e-scooters, and carshare as well as traditional modes of travel such as public transit and for developing tailored policies for different segments. Morton et al. (2017) used cluster analysis to divide individuals into five unique segments based on their preferences for EVs, socio-demographic characteristics, psychographic profiles, and other factors, arguing that policy interventions at the segment level rather than on the overall market level are important. Rafiq and McNally (2023) divided ridehailing users into four classes and explored the socio-demographics of those classes to understand the travel behavior patterns of different types of ridehailing users. A study by Lee et al. (2022) involving cluster analysis of ridehailing users also suggested tailoring policy responses based on the socio-demographics and land use attributes associated with the clusters. Cluster analysis has also been used in several studies to segment car-share users (Baumgarte et al., 2021; Burghard and Dütschke, 2019), and has been widely used to understand the intention to use traditional public transport (Şimşekoğlu et al., 2015) as well as to understand needs and preferences concerning the quality of service of public transit as a way to personalize marketing (de Oña et al., 2016). Specific to micromobility, at least one study has used cluster analysis to classify e-scooter users and provided suggestions for business development strategies for the mode (Degele et al., 2018). The method has also been used for understanding the customer segments of emerging mobility business models such as mobility as a service (MaaS) (Alonso-González et al., 2020).

Although numerous transportation studies have used cluster analysis to segment the market for the purpose of tailoring policies for different target groups, there are some limitations associated with this method (Kumar and Toshniwal, 2015). Clustering is a way to partition the market. This method was limited to providing a clear group differentiation and also lacked clarity about the relationships between variables that create the clusters. If the goal is to achieve a certain policy objective (e.g., increase in bike-share ridership) and to ensure equity outcomes for different socio-demographic groups (e.g., income, race, gender, etc.), relying only on cluster analysis may not be enough. A clearer picture can be obtained by combining cluster analysis with other complementary methods that can provide an effect size for each factor associated with different clusters with respect to different policy objectives. Association rule mining is often used to discern the relationships between variables that are the target of examination that several transportation-related studies used previously (Hossain et al., 2022; Xu et al., 2018). In this way, association rule mining can complement cluster analysis and both can provide a clearer picture of different market segments.

3. Methods

3.1. Study area context

The focus of this study is on the users of the Jump-operated electric

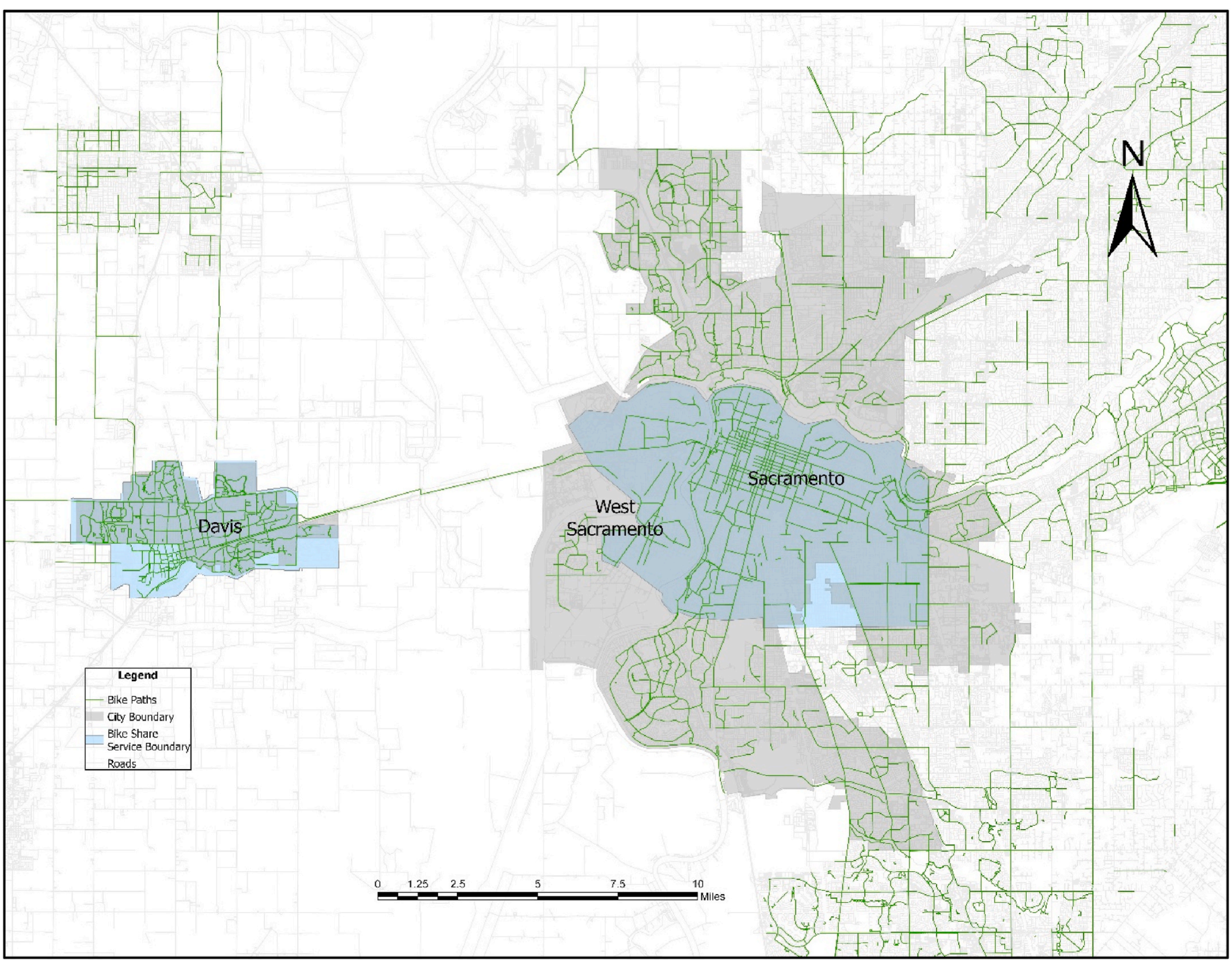

Fig. 1. Study area map with bike-share service boundary.

bike-share service in the greater Sacramento region that launched in the summer of 2018. By May 2019, almost 1000 e-bikes were available in Sacramento, West Sacramento, and Davis (100 e-scooters were also available in Sacramento and West Sacramento but we analyze only bike-share). The service covered an area of approximately 50 square miles, though the service areas were not all contiguous, Davis being separated from West Sacramento by about 10 miles. The study area map in Fig. 1 shows the bike-share service boundary. Davis is home to the University of California, Davis and has a rich history of bicycling (Buehler and Handy, 2008), but the official interest in bicycling in West Sacramento and Sacramento is relatively recent. In addition, the density of bike infrastructure such as bicycle lanes and cycle tracks (i.e., cycleways in Fig. 1) are much higher in Davis than in the other two cities. The bike-share service area in Sacramento is more urban in nature compared to the service areas in suburban West Sacramento and Davis. These three cities differ in terms of demographics, built environment, and employment activity.

3.2. Data collection

We collected data on bike-share users through a two-wave longitudinal survey as a part of a broader evaluation of the dockless electric bike-share. The two bike-share user surveys were conducted in October 2018 and May 2019, 4 and 11 months after the service began. The second survey was a follow-up with respondents from the first wave of the survey and included some newly recruited bike-share users. The survey was approved by the Internal Review Board of the University of California, Davis; participation in the survey was accepted as an indication of informed consent. Participant recruitment was done by intercepting users in the study area, taping fliers to bike seats with the URL and QR code for the survey, and for the first wave recruitment only, running Facebook advertisements run by the bike-share operator on our behalf on targeted zip codes. We based our field recruitment strategy on maximizing the number of users intercepted as well as attempting to recruit users across all geographies and times of day to ensure that the sample included people using the service in a variety of different ways. Table 1 provides a summary of the key survey sample statistics compared to the characteristics of all residents in the study area.

3.3. Analysis methods

The analysis method has three parts. Fig. 2 shows how the different methods align with the three research questions. The analysis is sequential as the answer to one research question feeds into the next.

First, the market segmentation analysis segments the bike-share users into different clusters/segments based on their perceptions of the service, mode use behavior, and use purpose of the service. The results of these segmentation approaches raised concerns for social equity based on how selected groups who struggle to afford transportation and/or who cannot own or use a personal car falling into different segments.

Second, descriptive analysis of the market segments provides insights into the presence of different transport-disadvantaged groups in the different market segments. This analysis shows the importance of understanding the combination of sociodemographic characteristics of a user. In addition, analysis of detailed individual-level data from surveys of bike-share users forms a basis for developing equitable bike-share-related policies.

Third, the last analysis is the use of association rule mining to provide the concrete probability of being in a specific use frequency group (i.e., minimal, infrequent, frequent, and super user) for different combinations of socio-demographic characteristics. In this portion of the analysis, we focus on the question of achieving social equity while growing the demand for bike-share at the same time. The probability values show how likely low-income, zero-car owners and students are to be in the frequent and super user groups. These probability values thus help in targeted marketing to both boost bike-share ridership while also addressing social equity.

Table 1
Socio-demographic characteristics s of bike-share users and study areas.

Variable		Bike-share User Survey	Davis	Sacramento	West Sacramento
Population			68,640	503,482	53,151
Sample size	Wave 1	462			
	Wave 2	409			
Enrolled student		25 %	51%	25%	28%
Races	White	65 %	63%	44%	63%
	Black	4 %	3%	14%	5%
	Hispanic	13 %	13%	28%	33%
	Asian	18 %	23%	19%	12%
Education status	College education	76%	75%	34%	30%
	No college education	24%	25%	66%	70%
Age	(median)	33	25.5	36.2	34.3
Gender	Woman	41 %	54%	51%	51%
Household income[a]	Low Income[b]	20 %	39%	39%	36%
	Middle Income[b]	57 %	36%	44%	48%
	High Income[b]	23 %	25%	17%	16%
Auto ownership	Non-auto owner	14%	4%	4%	3%

Note.
[a] The income classification measurement can be found in the California Poverty Measure (CPM) (Public Policy Institute of California & Stanford Center on Poverty and Inequality, 2023)and in kidsdata.org (KidsData, 2023).
[b] As the income in California is different than in other parts of the US and as our Income data is collected on different income categories, we further categorized the different income categories as Low Income: Personal income ≤ \$25,000 or household income ≤ \$50,000, Middle Income: Personal income between \$25,000 to \$100,000 or household income \$50,000 to \$150,000.

3.3.1. Market segment analysis

We performed two different types of market segmentation analysis, namely, psychometric and behavioral segmentation, with two versions of the latter, using the sets of variables listed in Table 2. For the psychometric segmentation, we conducted a cluster analysis using different types of latent perception variables of the bike-share service as described in Table 2. For the first behavioral analysis, we segmented the users based on their use of bike-share for commuting and various non-commuting purposes. For the second behavioral analysis, we classified individuals into different mode use pattern groups based on how many days in a week they use different modes (i.e., walk, bike, transit, car alone/drive alone, and car passenger) for commuting purposes. For instance, an individual can be quasi-unimodal (i.e., individuals who use a car for the majority of their trips) or multimodal (i.e., individuals who use different types of modes for making their trips).

In cluster analysis, segmentation is done based on the distance measures of specific factors between the individuals. For the perceptions of different aspects of bike-share analysis (Table 2), we converted the Likert-type statement responses into equal interval scores and used those to perform the cluster analysis. We coded “strongly disagree” to 1, “disagree” to 2, and so on for each statement. Then, we used those response scores for each individual to calculate the distance between individuals for a selected number of variables in each cluster analysis. We measured the distance between respondents through the following **equation (1)** where X_i and X_j are respondents, D_{ij} is the Euclidean distance between two respondents, and k is the number of clusters.

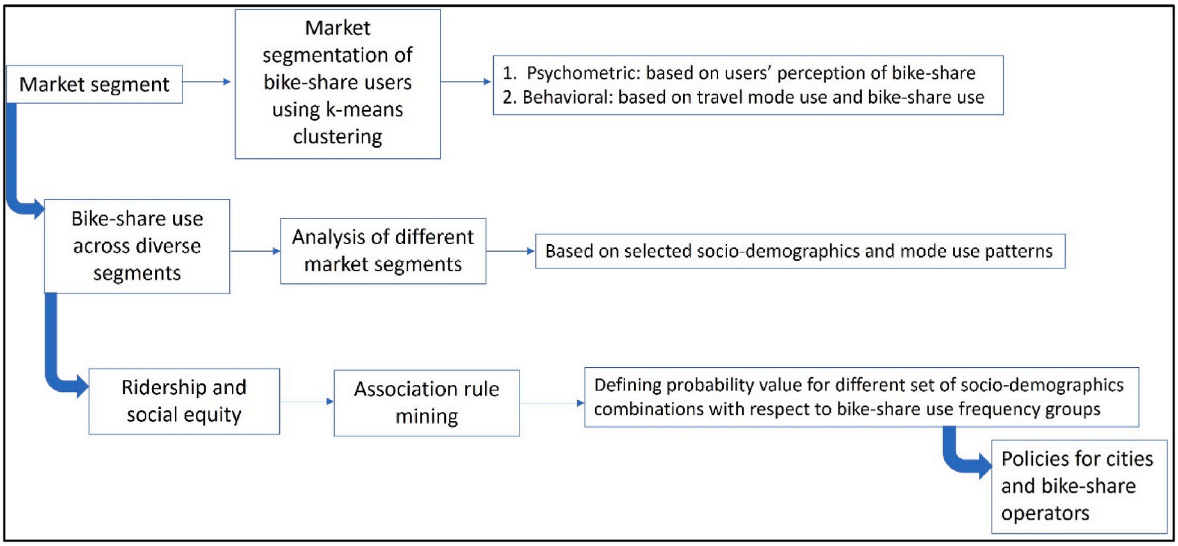

Fig. 2. Methodological flow diagram.

Table 2
Variables used for the market segmentation process.

Perception of different aspects of the bike-share service[a]	**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
Use of bike-share for different purposes[b]	Mean score (on a scale of 1–5)
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
Use of mode for commuting[c]	Mean score (on a range of 1–7 days)
Walking for more than 10 min at a time	2.20
Bicycling (personal and bike-share)	2.87
Taking public transit (for example, a bus or train)	2.13
Driving yourself	2.68
Riding as a passenger with someone else	1.90

[a] For each statement in the table, 1 indicated "strongly disagree"; 2, "disagree", etc. The response to these statements was collected on a 5-point Likert-type scale.
[b] For categories order is: Never or Less than one trip a month (1), 1–3 trips a month (2), 1–2 trips a week (3), 3–4 trips a week (4), and 5+ trips a week (5).
[c] How many days in a typical week individuals used the mode.

$$D_{ij} = \sqrt{\sum_{k=1}^{k} (X_{jk} - X_{ik})^2} \quad (1)$$

We selected a non-hierarchal clustering method as we have a large enough sample of bike-share users (Kumar et al., 2018). Specifically, we used the K-means approach to segment the bike-share users. In this method, the clusters are defined so that the total intra-cluster variations are minimized. The standard algorithm used for K-means clustering is the Hartigan-Wong algorithm (1979) which determines the total within-cluster variation as the sum of squared distances between items and the corresponding centroid using the following equation (2) (Hartigan and Wong, 1979).

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2 \quad (2)$$

Where x_i is a data point belonging to the cluster C_k and μ_k is the mean value of the points assigned to the cluster C_k. While making the clusters, each observation (x_i) is assigned to a given cluster such that the sum of squares distance of the observation to their assigned cluster center μ_k is minimized. The total within-cluster sum of squares measures the goodness of the clustering process. The total within-cluster variation is calculated by the following equation (3).

$$\text{Total within cluster variation} = \sum_{k=1}^{k} W(C_k) = \sum_{k=1}^{k} \sum_{x_i \in C_k} (x_i - \mu_k)^2 \quad (3)$$

In the k-means clustering method, the researcher has to define the number of clusters to be extracted from the data. We determined the number of clusters 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). Based on the results of the three threshold 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).

After segmenting the bike-share users using the three approaches outlined in Table 2, we analyzed each segment as to socio-demographic characteristics, including the percent of women, students, white, college-educated, employed, users having kids, and non-auto owners. We also report percent by income score (mean of categories converted to an equal-interval score namely, low-income (1), middle income (2), and high income (3)) in each segment. For each segment, we also report percent by age score (mean of categories converted to equal interval score namely, age 15 to 25 (1), age 26 to 35(2), age 36 to 45(3), age 46 to 55 (4), and age more than 55(5)). To examine the use of the bike-share system by segment, we analyzed the average number of bike-share trips (in the last 28 days). We analyzed the use of other modes by calculating a biking, car-share use, and ridehail use score (mean of categories converted to equal-interval score namely, never or not used in last year (1), a few times per year (2), a few times per month (3), a few times per week or every day or almost every day (4)). We present the results using radar plots.

3.3.2. Association rule mining

In addition to the market segmentation analysis, we conducted an association rule analysis, a data mining approach, to extract a set of characteristics of a specific bike-share group of interest. Specifically, we divided the bike-share users into super users, frequent users, and infrequent users. We then applied association rule mining to extract the socio-demographic characteristics of super users and frequent users. After doing market segmentation/cluster analysis based on different attributes of users, association rule mining will suggest the association between attributes that are more likely to a specific type of bike-share user group (i.e., a person who is low-income and zero-car owner are a certain % more likely to be a frequent user than a user chosen in random). Both of this information is important for cities, transportation agencies, and bike-share operators to assist them to understand the different segment of users, their attributes, and how that information can be used to achieve social equity as well as an increase in ridership.

The association rule mining method can be effectively applied to customer datasets to understand customer characteristics. For association rule analysis, two things need to be defined: an item and a rule. For instance, in a bike-share user customer database that contains customer socio-demographic information (e.g., married status, gender, car ownership status, etc.) and bike-share use status (super user, frequent user, infrequent user, etc.), an item can be "gender = male" and a rule can be "gender = male - > bike-share user status = frequent user". A rule can also have a combination of items (e.g., socio-demographics) such as "gender = male, income = middle income, car ownership status = no - > bike-share user status = frequent user". We can define the socio-demographics combinations as the left side (L), the variable category that we are interested in as the right side I, and use an arrow sign to connect those to show that it is a rule. Generally, three-parameter values are reported for understanding the quality of a rule: support, confidence, and lift. The support for such type of data set for the L → R is

$$\text{Support} = \frac{\text{number of rows containingLandR}}{\text{total number of rows}} = P(L \text{ and } R) \tag{4}$$

The confidence for this rule is:

$$\text{Confidence} = \frac{\text{number of rows containingLandR}}{\text{number of rows containingL}} = P(L|R) \tag{5}$$

The lift for this rule is:

$$\text{Lift} = \frac{\textit{Confidence for the rule}}{P\ (R)} = \text{I} = \frac{\text{P(LandR)}}{\text{I)} * \text{P(R}}\Bigg) \tag{6}$$

Support measures the probability of having both the left side and right side of a rule together in the dataset rows. We used a minimum support value of 0.03 (i.e., item set at least present in 3% of the observations considered to be part of analyses) to search the most frequent item sets in our bike-share user dataset. This will ensure we do not only get a socio-demographic combination set of bike-share users that just happened in some instances and does not have marketing implications. This process is computationally intensive. A commonly used algorithm used to accomplish this process is the Apriori algorithm (Agrawal and Srikant, 1994). However, frequent pattern mining algorithms give more computational efficiency with similar results which we used in this study (Han et al., 2000).

Association rule analysis is helpful in our analysis of bike-share users as these values indicate how probable it is that an individual with a given set of characteristics will become a specific type of bike-share user. For the example provided, a lift value of 1.1 for a rule indicates that a person having a single socio-demographic attribute or a person having a combination of socio-demographic attributes–is (1.1 - 1) *100 or 10% more likely to be a frequent bike-share user than a user chosen at random.

3.4. Methods of handling missing data

Both the household survey and 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. We then used the combined dataset consisting of these 20 datasets for our market segmentation analyses.

3.5. Limitations

Because our recruiting method for the bike-share user survey included intercepting, the sample may potentially be biased toward people who bicycle more regularly. We provide a comparison of the socio-demographic characteristics of the bike-share users in our sample with those of the population of the study area. A large portion of our user sample is middle income and a very low portion is low-income, consistent with at least one previous study (Shaheen et al., 2014). 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.

4. Results and discussion

4.1. Psychometric segmentation

We extracted three different segments based on the responses to the bike-share-related perception statements described in Table 2. A segment, also referred to as a cluster throughout this article, is assumed to be a collection of individuals all of whom are behaviorally similar from the perspective of the researcher. The socio-demographic and mode-use pattern analysis for the clusters is shown in the upper radar plot in Fig. 3. The lower radar plot shows the differences in clusters with respect to their different perceptions of the bike-share service. The radar plots illustrate 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.

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 perception of the bike-share service. The high score on the *hard-to-find parking* (for the bike) and a low score on the *bike usually available* perception statements indicate that frequent users of bike-share are 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. Compared to the other two clusters, individuals in this cluster have lower incomes. Car ownership is the lowest in this cluster, personal bicycling use is low, transit use is moderate, and use of car-share services is high. As this cluster uses bike-share frequently and bicycles in general at a very low rate, it can be assumed that bike-share is promoting bicycling in this cluster.

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

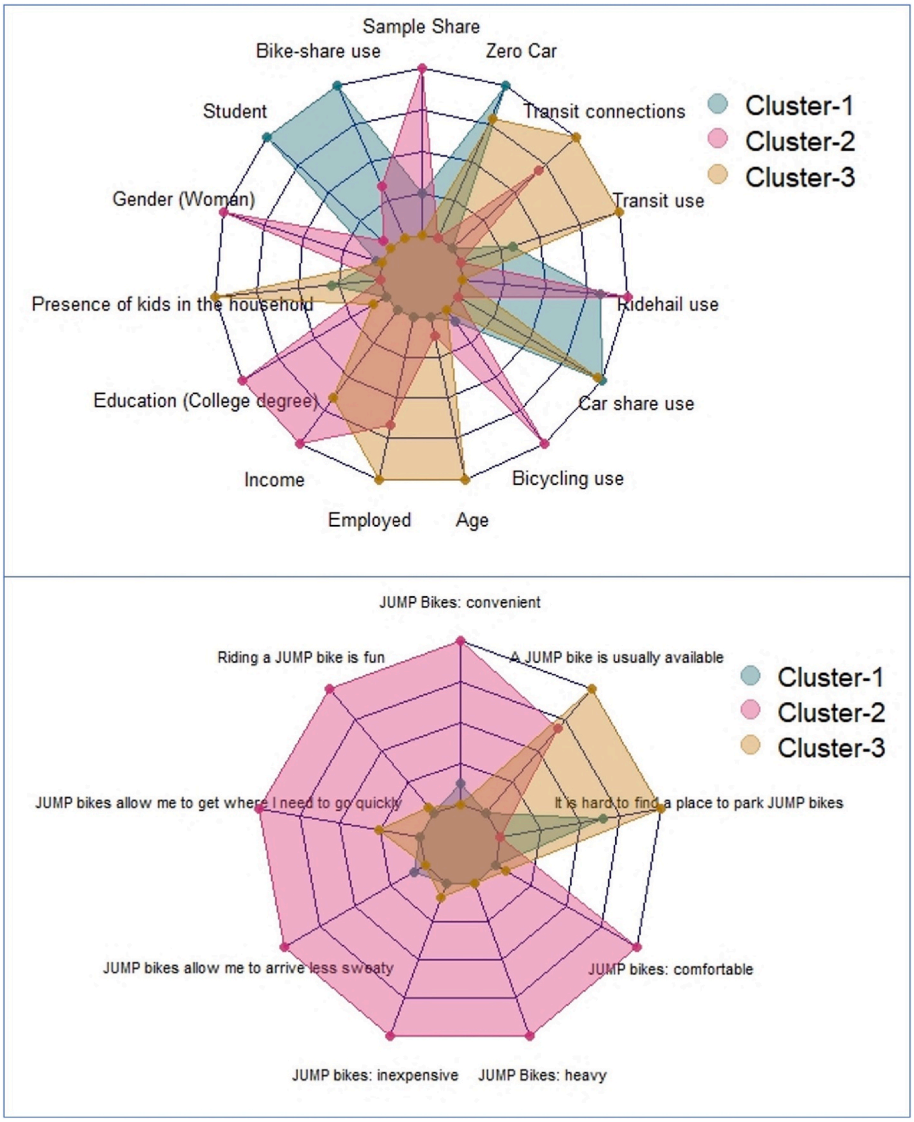

Fig. 3. Market segments based on users' perception of bike-share service.

greater use: members of this segment use the service at a moderate rate. We call this the "satisfied user" cluster. Compared to the other two clusters, individuals in this cluster have higher incomes. In addition to being moderate users of the bike-share service, this cluster uses personal bikes more frequently than the other two clusters and has a high car ownership rate. In addition, individuals in this cluster use ridehailing services at a higher rate compared to others. This user cluster consists of a higher proportion of college-educated 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 cluster 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 are often using it to connect to transit. The members of this cluster can be a potential market for bike-share due to their lower car availability; however, targeting this cluster should involve providing them with 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.

4.2. Behavioral segmentation

4.2.1. Market segments based on the bike-share use purpose

We classified bike-share users into four clusters based on their bike-share use for commuting and different non-commuting purposes. The characteristics of different clusters are shown in Fig. 4.

Cluster 3 is the largest segment 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. However, this cluster uses personal bicycle at a moderate rate. This cluster has the lowest proportion of the student population and has higher incomes compared to others. Their transit use rate is the lowest and car ownership rate is the highest among others.

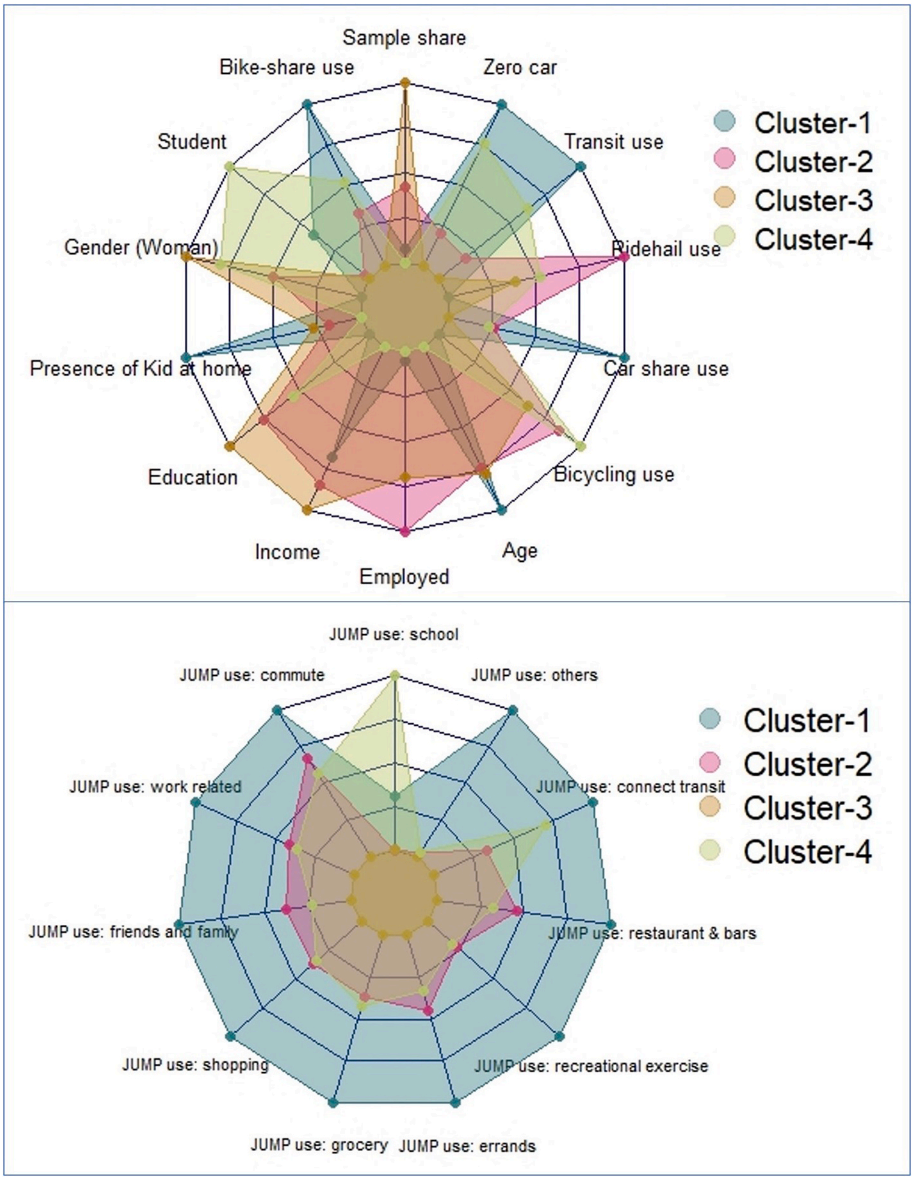

Fig. 4. Market segments based on the use of bike-share for different travel purposes.

Cluster 4 is the smallest segment of users (9% 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 cluster mainly consists of students, so we call this the "school" cluster. This cluster also uses personal bikes and ridehail at much greater rates compared to others, consistent with the fact that more than half of this cluster 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 members consist of 11% of the sample and use bike-share at the highest rate. This cluster has the highest average frequency for most 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 cluster are students. This group also consists of lower-income, carless individuals who are most likely to be a user of transit and carshare. Although this cluster has very low car ownership, the use of ride-hailing by this cluster is still the lowest among the four clusters, a result that may be due to the high cost of ride-hailing. This cluster 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 cluster to ride bikes.

Cluster 2 is the second largest segment (27% of the sample). They use bike-share moderately frequently. Their use of bike-share for commuting, going to restaurants and bars, and doing their 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 cluster. This cluster 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 cluster have cars, it is not surprising that their use of transit and carshare is limited. This cluster 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.

4.2.2. Market segments based on mode use patterns for commuting

We analyzed bike-share market segments by mode use patterns for commuting, where mode use patterns are based on what mode or modes individuals regularly use for commuting purposes. We extracted three clusters that represent distinct mode-use pattern classes. The characteristics of the different mode-use pattern clusters are shown in Fig. 5 in a format similar to the previous market segmentation analyses.

Cluster 3 is the smallest cluster (16% of the sample) and has a very high rate of bike-share use. This cluster 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 segment has a very high share of members who do not own cars. The member of this cluster has the lowest income among the three clusters. 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 cluster 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 likely to be limited to non-commuting trips, and the zero-car ownership rate of this cluster is exceptionally low (1%). In addition, this cluster consists of a higher proportion of middle and high-income individuals. 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 cluster 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 may mainly use bikes for their entire commute. Carless individuals make up a considerable portion of this cluster. Individuals with similar characteristics who are not already using bike-share are a promising potential market for bike-share as a commute mode.

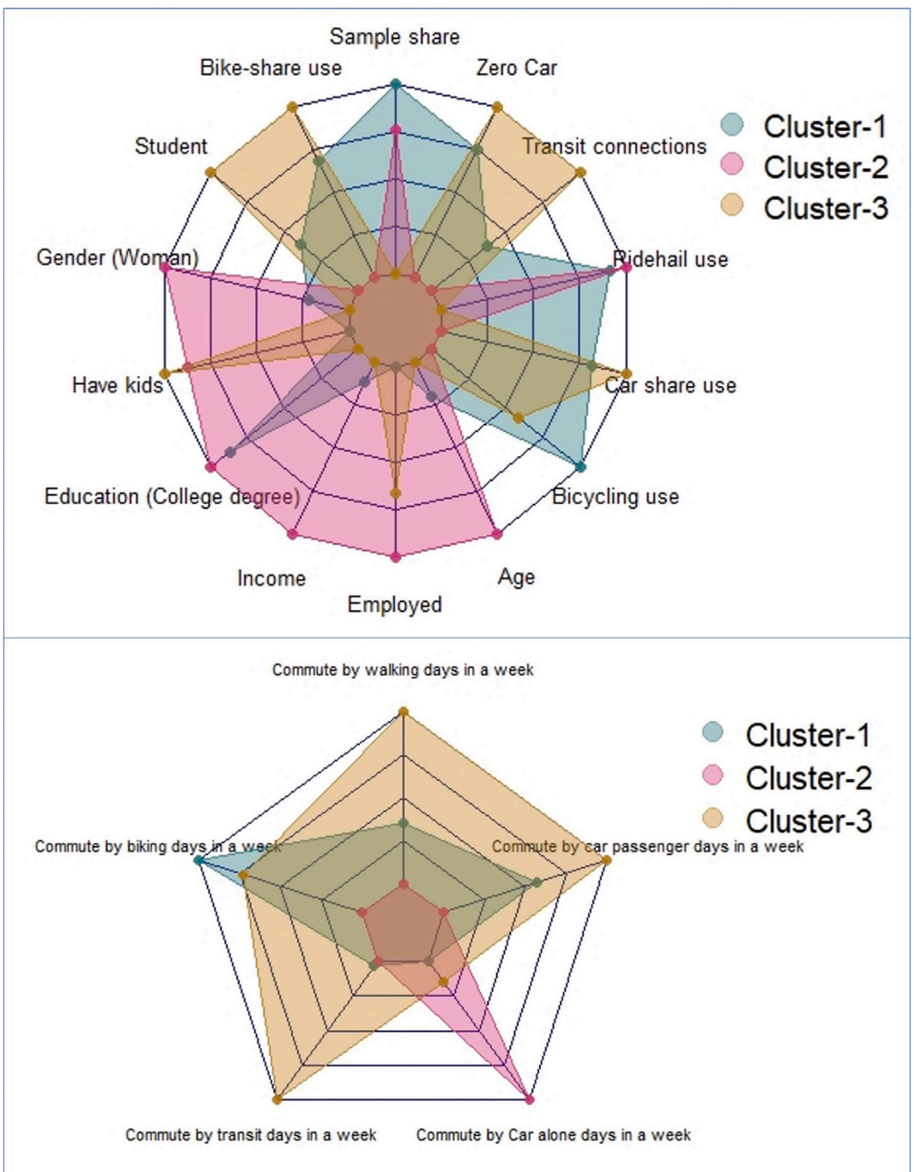

Fig. 5. Market segments based on mode use patterns.

4.3. Implications of the bike-share market segments on demand and equity

4.3.1. Social equity implications

Both types of market segmentation analysis indicate that bike-share services are adopted by all socio-demographic groups. A large portion of low-income and zero-car users appear to use the service at higher rates even though these groups of users may not be fully satisfied with certain aspects of the service compared to others (see the "disgruntled users" cluster described above). More favorable perceptions of the service may not translate into higher use as middle- and high-income, college-educated individuals have more favorable perceptions but use the service less frequently (see "Satisfied user" cluster). A higher share of low-income and zero-car users are also using the service for a wide variety of purposes compared to others (see the "multi-purpose user" cluster). Multimodal users (e.g., users who also use transit, bikes, car-share, etc.) use the service at a higher frequency compared to others (see the "transit user", "disgruntled users", and "super multimodal" clusters). At the same time, a higher share of car owners, unimodal car users, and higher-income individuals are using the bike-share service at a very low rate compared to others. These findings point to the importance for social equity of the bike-share service, which provides an additional mobility option for the segments of the population who struggle to afford transportation, who cannot own or use a personal car, and who are likely to have fewer available mobility options. Promoting bike share to the people who need it the most is a way to address social equity and boost the demand for the service at the same time.

4.3.2. Implications for user recruitment for increasing demand

The market segmentation analyses suggest that a large portion of individuals who are zero car owners, low-income, and students are using the service at a high rate compared to others. Although this provides some guidance for the operator, a better and clearer rule-based set of individual characteristics can help the bike-share operator to efficiently target new users who are likely to use the service frequently and entice them to adopt the service. We used the association rule mining approach that marketing researcher sometimes uses to determine target customers. We divided the bike-share users into four classes based on their use frequency as described in Table 3. Bike-share operators are likely to be interested in the "super user" and "frequent user" groups as having a high proportion of such individuals in the user base would boost the demand for the service. Cities and other authorities who are concerned about social equity, on the other hand, are likely to be interested in achieving a high proportion of transport-disadvantaged groups in the user base as these groups especially benefit from the enhanced accessibility to opportunities the service provides. We generated several "rules" for the frequency categories using the association rule mining method, in the sense of what demographic combinations promotional efforts should focus on to increase the number of users in that frequency category. We then examine how to achieve a boost in bike-share ridership while addressing social equity. We provide the top five rules for each type of bike-share user category based on their lift value (described in the method section of this article) in Table 3.

Table 3
Top five rules for a frequent user, super user, infrequent user, and minimal user of bike-share.

Super User (more than 40 trips in the last 28 days)	Lift
Employed, White, Man	1.45
White, Man	1.38
Employed, Man	1.30
Man	1.29
College Education, Man	1.26
Frequent User (21–40 trips in the 28 days period)	
Zero-Car Owner	1.59
Low Income, No Kids	1.59
Low Income	1.51
No College Education, No Kids	1.50
Student, No Kids	1.47
Infrequent User (2–21 trips in the last 28 days)	
Age 36 to 45, Man, High Income, Auto Owner, Non-Student, White	1.31
Age 36 to 45, Man, High Income, Auto Owner, White	1.30
Age 36 to 45, Man, High Income, Non-Student, White	1.30
High Income, Age 36 to 45, White, Man	1.30
Non-Student, No Kids, White, Age 46 to 55	1.30
Minimal User (0 or 1 trip in the last 28 days)	
High Income, Auto Owner, Woman	2.10
High Income, College Education, Auto Owner, Woman	2.07
High Income, Woman	2.04
High Income, College Education, Woman	2.01
High Income, Non-Student, Auto Owner, Woman	2.01

The results provided in Table 3 are mostly aligned with the market segmentation analysis. However, these rule sets indicate how probable an individual with a set of characteristics is to become a specific type of bike-share user. For instance, based on the interpretation of the lift value described in the method section, a lower-income user is 51% more likely to be a frequent user of bike-share than a user chosen at random. A zero-car owner user is 59% more likely to be a frequent user of bike-share than a user chosen at random. A low-income user who does not have any kids is 59% more likely to be a frequent user of bike-share than a user chosen at random. A user who is high-income, non-student, and white with an age between 36 and 45 is 31% more likely to be an infrequent user than a user chosen at random. The minimal user group rules have very high lift values. High-income women who own cars are 110% more likely to be in the minimal user category than a user chosen at random. This indicates that a significant portion of the female population may not find this service useful to them.

These findings, with probability values for each rule, give bike-share operators a clear idea of whom they should target for newer user recruitment if they want to boost demand. As bike-share operators may have limited budgets for newer user recruitment, they can use the probability values to prioritize which groups they should prioritize to boost the demand. Table 3 shows that targeting lower-income, zero-car owners, and students for newer users' recruitment are more likely to boost long-term bike-share ridership as these groups are more likely to be frequent and/or super users. This finding also indicates that bike-share operators can grow their demand while addressing social equity as these groups of the population are likely to have fewer transportation options. These findings are also important sources of information for cities and transportation authorities who are more concerned about achieving equity by developing policies for operators of the emerging transportation technologies in the current transportation landscape.

5. Conclusion and policy implications

In this study, we segmented the bike-share user market in the greater Sacramento region, California, USA based on their perceptions of the bike-share service, their use of bike-share for different travel purposes, and their general mode use patterns. Market segment analysis shows that it is not the satisfied users but rather the disgruntled users who are using the service at a higher rate indicating that frequent use may be driven by the need for the service. This finding has policy implications as it indicates that improvement of the service may be important for marketing but more important is to provide adequate access to the service to those who need it for different travel purposes. With the findings of this study, cities and other authorities can collaborate with bike-share operators to formulate policies to address the needs of transport disadvantaged groups.

Other insights emerged from the analysis. The transit cluster uses the service at a high rate for connecting to transit, but their overall use of the service is low. The multipurpose user cluster and the school cluster use bike-share at a high rate although they represent a small share (around 21%) of all users. Utilitarian clusters use the service at a moderate rate for some specific trip purposes. The dabblers cluster, which consists of more than half of all users, uses the service at a low rate for most purposes. Bike-share is generally adopted by all types of mode user clusters but is used at a higher rate by the super multi-modal and active multimodal clusters. The super multi-modal cluster (a segment that uses a combination of different modes) is using the service at the highest rate but consists of a very low proportion of users. These results suggest that different segments of bike-share users may have different needs and that they use the service for different purposes. Using this knowledge, bike-share operators can tailor their marketing strategy for each group, and transportation planners can tailor urban transport policies (Morton, 2018), particularly to encourage multimodality and car-lite lifestyles. For instance, the "transit user" segment can be of special interest to transit agencies in their effort to ensure that bike-share complements rather than substitutes for transit. The "disgruntled" cluster uses the bike-share with high frequency but bicycles in general at a low rate, while the bike-share use purpose analysis revealed a "multi-purpose" cluster that uses bike-share for a variety of purposes but bicycles in general at a low rate. These are important market segments that may not be fond of using personal bikes but are interested in using electric shared bikes; targeting people like them who are not yet using the service could lead to a substantial increase in bike-share users and overall bike-share use.

Along with the market segment analysis, the association rule analysis provided specific sets of socio-demographic characteristics that bike-share operators can target. The probability values for the different socio-demographic combinations of bike-share users suggest that bike-share operators should target low-income, zero-car owners, and students for new recruitment as these groups are more likely to use bike-share frequently. As these groups are likely to have fewer transportation options and/or struggle to own and maintain a car, this approach will both boost demand as well as address social equity. One notable finding is that women are less likely than men to use the bike-share service. This is consistent with previous studies on bicycling that show that women are less likely than men to bicycle (Pucher and Buehler, 2008; Sahlqvist and Heesch, 2011; Sustran, 2018). Further research is needed to understand if women face barriers to bike-share use beyond the gender gap in bicycling.

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. The findings from our study suggest that bike-share operators may want to rethink their service distribution strategy, as previous research has shown that bike-share stations in North America are more likely to be located in wealthier neighborhoods (Hosford and Winters, 2018; Ursaki and Aultman-Hall, 2016). Operators can consider promoting bike-share use in areas that have a higher proportion of low-income and zero-car households as a way to recruit new users. Cities can collaborate with bike-share operators to provide initial discounts for transport-disadvantaged communities and extensive marketing of these discounts as suggested by Dill and McNeil (2021).

More work is needed to better understand some of the important clusters identified in this study in other markets and explore the effectiveness of bike-share implementation in achieving transportation equity and sustainability goals. Future research should explore the 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.

Author contributions

The authors confirm their contribution to the paper as follows: study conception and design: SH, DF; data collection: DF, SH; analysis and interpretation of results: HM, DF, SH; draft manuscript preparation: HM, DF, SH. All authors reviewed the results and approved the final version of the manuscript.

Declaration of competing interest

The authors do not have any conflicts of interest to declare.

Data availability

Data will be made available on request.

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