Journal of Transport Geography 109 (2023) 103588

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Does bike-share enhance transport equity? Evidence from the Sacramento, California region

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A R T I C L E I N F O

Keywords:
Electric bike-share
Equity
Bike-share use purpose
Transport-disadvantaged groups
Statistical modeling

A B S T R A C T

As bike-share systems proliferate across the US, their potential as a way of expanding opportunities for those most underserved by the transportation system merits a deeper understanding of its current users. In this study, we examine the rate of bike-share adoption by individuals from different socio-demographic groups and living in different bicycling contexts. We explore how individuals incorporate bike-share service into their travel patterns for different travel purposes and change their use of other modes. Data are from a two-wave survey of bike-share users and a parallel household survey of residents in the Sacramento region. Our modeling results for bike-share adoption and use frequency show that low-income individuals are less likely to adopt bike-share but use the service more frequently than other income groups when they do adopt. Low-income users, people of color, and non-auto owners are more likely than other groups to use bike-share frequently for many trip purposes. Individuals living in areas with a stronger biking culture and surrounded by bike infrastructure are less likely to adopt the service and less likely to use it for purposes other than commuting. All users change their use of other modes when they incorporate bike-share into their travel patterns, but low-income individuals, people of color, and non-auto owners would be more severely impacted if the service were to stop. Our results add new insights into the use of bike-share, a service that can enhance social equity while also addressing sustainability.

1. Introduction

Over the last decade, bike-share systems have attracted substantial ridership, even in the U.S.. (National Association of City Transportation Officials, 2020). Bike-share use often substitutes for car use (Fuller et al., 2013; Hsu et al., 2018), and even though this occurs mostly for relatively short-distance trips, the benefits for the environment are notable (Fukushige et al., 2021). Bike-share systems can also play a role in supporting rather than competing with transit by providing an option for the first or last leg of the transit trip (Mohiuddin, 2021; Oeschger et al., 2020; Shaheen and Chan, 2016). When used to connect to transit, bike-share has even more potential to substitute for driving (Grosshuesch, 2020; Jäppinen et al., 2013; Møller and Simlett, 2020). One study shows that bike-share may even have an indirect impact on overall bicycling by increasing the use of personal bicycles (Fitch et al., 2021). In sum, bike-share can decrease car travel, enable more multimodal trips, and provide mobility opportunities for individuals who have fewer transportation options.

The potential importance of bike-share as a way of expanding opportunities for those most disadvantaged by the transportation system merits a deeper understanding of its current users. These disadvantaged groups include low-income individuals for whom car ownership and even transit services are a financial hardship as well as zero-car households that do not have access to a car, whether by choice or owing to cost or other constraints. The introduction of bike-share has expanded their transportation options. The more recent introduction of electric bike-share may further expand these opportunities. Bike-share operators adopted the technology for attracting new segments of bike riders as well as improving the experiences of the existing ones as it gives extra boosts while pedaling (Treviño, 2019). Electric bikes require less effort by the user, and faster speeds make e-bike share a viable choice for longer trips. Electric bike-share systems may be less affected by bad weather and more capable of competing with public transit and taxi services (Campbell et al., 2016; Guidon et al., 2019). Indeed, electric bike-share systems have been growing even more rapidly than conventional bike-share (Galatoulas et al., 2020). As of 2021, two-thirds of station-based bike share systems had electric bikes, and a quarter of all station-based system bikes in the US were electric (NACTO, 2022).

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https://doi.org/10.1016/j.jtrangeo.2023.103588
Received 22 July 2022; Received in revised form 19 March 2023; Accepted 14 April 2023
Available online 6 May 2023

However, several studies have reported that both conventional and electric bike-share users are mainly middle- and high-income and predominantly white (Mohiuddin et al., 2022; Oates et al., 2017; Shaheen et al., 2014; Wachsmuth et al., 2019).

The disproportionate use of bike-share services by higher-income individuals is partly due to the disproportionate siting of bike-share stations in wealthier neighborhoods (Hosford and Winters, 2018; Ursaki and Aultman-Hall, 2016). Although studies have examined the lower rate of bike-share adoption by low-income individuals, how they use the service when they do adopt it remains a question. Apart from socio-demographics, access to bike infrastructure can play a role in the use of bike-share (Guo et al., 2022). The composition of vehicles also seems to matter: A study in Philadelphia shows that the integration of electric bikes in the bike-share fleet increased the use of bike-share in disadvantaged communities (Caspi, 2022). A bike-share system improves social equity if it serves the travel needs of segments of the population who struggle to afford transportation and who cannot own or use a personal car.

The objective of this study is to assess the contribution of bike-share to enhancing transportation equity by exploring the use of the bike-share by transport-disadvantaged groups and the subsequent impact of the service on their travel patterns. In this study, we examine the rate of bike-share adoption by different socio-demographic groups in different bicycling contexts. We explore both how the bike-share service is used for different travel purposes and the relationship between bike-share and other modes as well as its impact of bike-share use on travel patterns more generally. Data are from a two-wave survey of e-bike-share users and a parallel household survey of residents in the Sacramento region. We focus on two groups considered to experience transportation disadvantage, individuals with low incomes and individuals who do not own a car, in comparison to other socio-demographic groups. Our research questions are:

Q1: Do different socio-demographic groups adopt the service at different rates? Are some socio-demographic groups over-represented among users compared to their share of the population?

Q2: How do the frequency and purpose of bike-share use vary across groups?

Q3: How do service adoption and use vary by the nature of the bicycling environment?

Q4: How does the impact of bike-share on travel patterns vary across groups?

This analysis produces insights into the ways that bike-share is serving transport-disadvantaged groups and provides a basis for efforts to enhance transportation equity while suggesting directions for future research.

2. Literature review

Previous studies have explored bike-share access, adoption, and purpose of use by different socio-demographic groups. Many studies have analyzed the spatial accessibility of the service, pointing to inequities for low-income neighborhoods and explaining, in part, their lower rate of adoption. Few studies have focused on the ways that low-income individuals and people of color use bike-share when they do adopt the service. Such studies are important for understanding the role that bike-share plays in the lives of these users, in terms of both the trip purposes for which bike-share is a useful mode of travel and which modes bike-share is superior to as a way of meeting travel needs. This is especially important in the US context where mobility is highly uneven by race with respect to quality of experience, commute times, access to transport infrastructure, among other factors (Sheller, 2018). It is important to note that most of the literature on bike-share equity examines conventional bike-share rather than e-bike share. Many questions about the role of bike-share and especially e-bike share in enhancing transportation equity remain.

Studies examining bike-share accessibility by income have found unequal spatial distribution. Bike-share stations in North America have tended to be located in wealthier neighborhoods (Babagoli et al., 2019; Duran-Rodas et al., 2021; Hosford and Winters, 2018; Ursaki and Aultman-Hall, 2016; Wachsmuth et al., 2019). Though the more recent dockless bike-share systems may have improved access to bike-share services relative to earlier systems constrained by the location of bike-share stations (Qian et al., 2020), the proper rebalancing of bikes to ensure equitable access is still an issue. Compounding the difference in access to bike-share services are differences across neighborhoods in the quality and extent of bicycle infrastructure, an important factor for both docked (Alcorn and Jiao, 2019; Buck and Buehler, 2012; Rixey, 2013; Zhao et al., 2021) and dockless bike-share (Lin et al., 2020; Shen et al., 2018).

Other studies have found bike-share access and use to be limited by income and by race. One study using bike-share membership data in the United States found that people of color, females, those who are low-income, those who are unemployed, and those with less education were underrepresented (Grasso et al., 2020). Another analysis of users from the Capital Bike-Share program in Washington DC found that users were mostly white (Stromberg, 2015). White users and those with higher incomes are often over-represented among users (McNeil et al., 2018; Shaheen et al., 2014). This unequal adoption rate may partly be due to the unequal spatial distribution of bikes across neighborhoods, as well as differences in population density and the presence of points of interest (Guo et al., 2022). The cost of access, lack of payment options, and lack of bank and credit card accounts also limit use by populations with limited financial means (McNeil et al., 2018).

Although several studies have examined the adoption of bike-share, analysis of sociodemographic differences in the trip purposes for which bike-share is used is rare. One study shows that neighborhoods with a higher percentage of socio-economically disadvantaged groups have higher bike-share use (Oates et al., 2017). Another study using Vancouver bike-share user data found that super users are more likely to be young, male individuals with incomes less than $75,000 and fewer transportation options (Winters et al., 2019). Rixey (2013), using socio-demographic data for the areas around bike-share stations, found that median income levels are positively associated with bike-share trips, and the percentage of non-white is negatively associated.

Bike-share studies in North America have mostly used system-level data to characterize the use of the service, providing limited analysis of the use of the service by socio-demographic characteristics. A study showed that members living in neighborhoods with a higher concentration of minority and lower socioeconomic status populations are likely to use bike-share frequently at varied times of day (Wang and Lindsey, 2019). Analyses of system-level trip data combined with built environment data have shown that bike-share users are more likely to cycle for utilitarian purposes (El-Assi et al., 2017), that the service is used for both utilitarian and recreational purposes (Wang et al., 2015), and that millennials are more likely to use bike-share for utilitarian purposes (Reilly et al., 2021). Another study using Washington DC data showed that bike-share is used for a wide variety of purposes (McKenzie, 2019). Using system-level data, however, to infer trip purpose and socio-demographic characteristics can mask individual-level relationships (the problem of "ecological fallacy") and does not provide the same insights into causal relationships that individual-level analysis can. The study by Wang and Lindsey (2019) has pointed to the need to collect detailed socio-demographic data of bike-share users. Just a few studies have done so, though they did not explore variation in trip purpose at the individual level (Shaheen et al., 2013).

The impact of bike-share on the use of other modes has been studied in general but not from an equity standpoint. Several studies have focused on mode substitution, that is, the question of what mode bike-share replaces, presumably because it is superior in some way. Research so far has focused on the car substitution question (Abouelela et al., 2021; Barbour et al., 2019; Bieliński et al., 2021; Fishman et al., 2014, 2015; Fukushige et al., 2021; Sun et al., 2020) or the transit substitution versus connection question (Campbell and Brakewood, 2017). In some cases, bike-share users make additional trips they would not otherwise have made; work by Fukushige et al. (2022) shows that the share of bike-share trips induced by the system ranges from 0% to 11%. In these ways, bike-share impacts the overall travel patterns of users.

Exploring changes in the use of other modes after adoption of bike-share can provide insights into the importance of bike-share in meeting travel needs. The influence of bike-share on individuals' car ownership status is another important question given the potential for bike-share to reduce financial hardship for some segments of the population.

3. Methods

3.1. Study area context

The focus of this study is the Jump-operated electric 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 mile^2, though the service areas were not all contiguous, Davis being separated from West Sacramento by about 10 miles. All three cities share a relatively flat topography, mild winters but hot summers, and an average of 20 in. of rainfall per year. While Davis has a rich history of bicycling (Buehler and Handy, 2008), West Sacramento and Sacramento have more recently focused on the needs of bicyclists. Fig. 1 shows a map of the study area. Davis has a very high density of bike infrastructure compared to the other cities. The Sacramento service area is more urban, while the West Sacramento and Davis areas are more suburban in nature. Davis is also home to the University of California, Davis. The selected cities also differ in terms of socio-demographics, road and bicycling infrastructure density, population density, and number of points of attractions as shown in Table 3. Some of these characteristics are important determinants of bike-share use (Guo et al., 2022).

The privately-owned Jump service was launched in the summer of 2018 and included approximately 900 electric-assist bicycles (e-bikes) as of November 2018 (100 to 200 of the bikes were not in circulation at any given time). By May 2019 the number of e-bikes increased to close to 1000, and 100 e-scooters were also available in Sacramento and West Sacramento but not Davis. Because the service predominantly provided e-bikes (and not e-scooters) and because we have collected a much richer set of data about e-bike use, we will refer to the bike-share service as "the service." The Jump service was dockless, meaning that the vehicles could be parked anywhere because they could be locked to themselves. Although the service was dockless, Jump installed some docks (including a few charging stations) to provide a location for rebalancing bikes, and users were sometimes incentivized to return

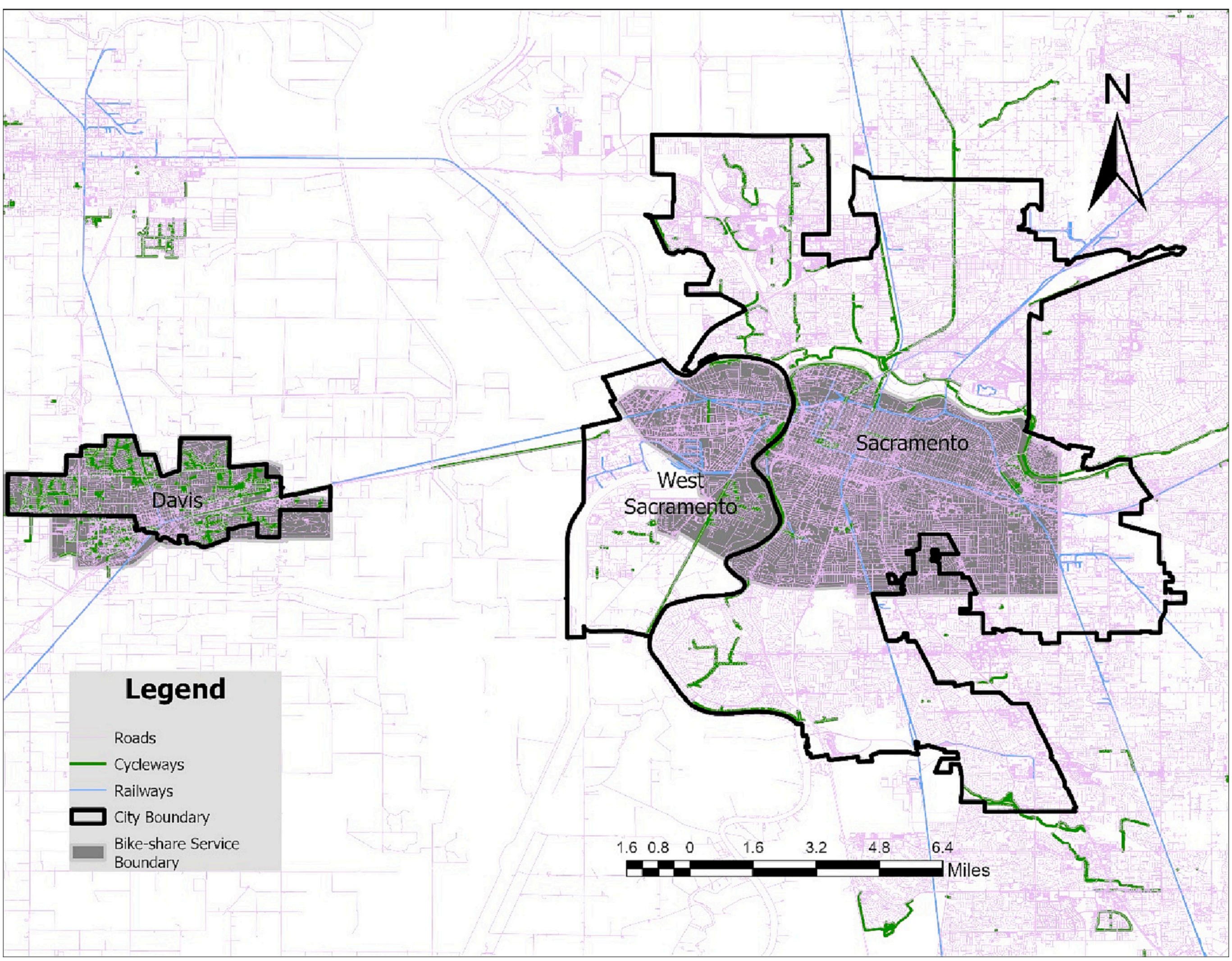

Fig. 1. Study area map.

bikes to the docks. We collected all survey data when Jump was the only micromobility service operator in the region, prior to when Lime opened an e-scooter share. Table 1 provides some of the major features of the Jump bike-share system in the Sacramento area.

3.2. Data collection

Data for this study come from a two-wave survey of users and from a parallel household survey of residents before and after bike-share arrived. All survey data were collected prior to the COVID-19 pandemic. 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.

The household survey was a repeat cross-sectional survey conducted before (2016) and after bike-share (May 2019) launched that used an address-based geographically stratified random sample (See (Fitch et al., 2020) for details). In this analysis, we only use data from the "after" survey on whether respondents had ever used the bike-share service. We used the household survey to answer the first part of the first research question and the third research question.

The bike-share user survey was a two-wave longitudinal survey of bike-share users in October 2018 and May 2019. The second survey was administered to the respondents from the first wave of the survey with the addition of some newly recruited bike-share users (a "refresh" of the panel). We recruited participants 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 for 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.

In addition to asking about use of the bike-share service, both surveys asked 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 analysis focuses on individuals experiencing transportation disadvantage, including low-income individuals and individuals who do not have access to a car. We define low-income individuals whose annual personal income is less than $25,000 or whose annual household income is less than $50,000. Non-auto owners include those who cannot afford as well as those who choose not to own a car.

Table 1
Sacramento region bike-share characteristics.

Bike-share characteristics	Description
Operational model	• Privately operated and owned by Uber • Phased implementation
Technology	• Dockless • Electric assistance • Limited docked charging stations
Access option	• Phone app (Jump or Uber) to reserve and check-out bikes • Pay Near Me program to enable cash payment to account • Call to Unlock for users without smartphones
Pay as you go	Pay as go: Unlock fee of $1.50 for 10 free minutes of ride time, $0.20 per minute thereafter
Subscription	$30 per month for 60 min of free ride per day
Student membership	$30 per year for 60 min per day
Equity program	BOOST membership: $5 sign up fee for first 12 months and $5 per month after that which gives 60 min of ride time per day to eligible low-income users
Redistribution	• $0.25 incentive to return the bike to any hub (proprietary parking rack) • $1 incentive to return the bike to any charging hub • Vans used for rebalancing
Parking	• Fee for bike parking outside the service area • > 600 bike racks within Sacramento (in 2018)
Popularity	Ranked 2nd in the world in terms of Jump bike and e-scooter use as of 2020

Sources: (Allison, 2019; Daniel, 2020; Daniels, 2019; Mckinney, 2018; Nowspeed, n.d.; Shannon, 2018).

3.3. Bike-share behavioral modeling

We used generalized linear regression models of *having used bike-share* and the *frequency of bike-share use* to examine differences in initial adoption and use of bike-share by sociodemographic groups. We modeled bike-share use for different activity purposes to understand how transport-disadvantaged groups are using the service for various travel purposes.

The models use a variety of predictor variables: socio-demographic characteristics include low-income status (defined above), gender, student status, race, employment status, having children, car ownership status, place of residence, and attitudes towards bikes and cars. We included two attitudinal indicators. The like-bike indicator is measured with these statements: "I like riding a bicycle," "Riding a bike is enjoyable," "Riding a bike is fun," and "Riding a bike is pleasant." The car-necessity indicator is measured with these statements: "I need my car to do many of the things I like to do" and "I need my car to carry shopping or children." The statements were measured by a 5-point ordinal scale ranging from 1 = "completely disagree" to 5 = "completely agree." The statements used to measure the attitudes were based on the previous study by Handy et al. (2010a) which used a five-point ordinal scale for the statements. Studies show that using a five-point scale is reliable for this type of analysis (Krosnick and Presser, 2009; Lissitz and Green, 1975). To increase the reliability of the measurement of attitudes, composite scales were constructed by summing up the items belonging to each category, averaging them, then rescaling them from 0 to 1 (Kroesen et al., 2017). Cronbach Alpha scores show an acceptable level of internal consistency for the statements for each indicator (Like-bike attitude = 0.93; car-necessity attitudes = 0.69).

Modeling "Used bike-share." This model uses data from the "after" household survey. The dependent variable was the response to the survey question, *"Have you ever used the Jump bike-share in the greater Sacramento area?"* with a binary "yes" and "no" response option. For simplicity, we refer to this as the bike-share adoption model. We estimate a binomial model (logistic regression) to determine which factors are likely to have large effects on bike-share adoption. Our model here is a model of log odds. If the probability of bike-share adoption is p, then odds are:

$$\text{Odds} = \frac{p}{1-p}$$

As p increases, so do the odds. The equation for the binomial regression is:

$$Y_i \sim \text{binomial}(p_i)$$

$$\begin{aligned} log\left(\frac{p}{1-p}\right) = & \beta_0 + \beta_1 City + \beta_2 Employment\ Status + \beta_3 College\ Education \\ & + \beta_4 Race + \beta_5 Student\ Status + \beta_6 Income\ Status + \beta_7 Gender \\ & + \beta_8 Age + \beta_9\ Having\ Kids + \beta_{10} Auto\ Ownership\ Status \\ & + \beta_{11} Like\ Bike\ Attitude + \beta_{12} Car\ Necessity\ Attitude \end{aligned} \tag{1}$$

Where β_0 is the mean probability and all beta parameters represent the contribution of each corresponding predictor variable of their products.

Modeling Bike-share Use Frequency. The dependent variable in this analysis is the response, from both waves of the bike-share user survey, to the question *"In the past 28 days, how many Jump [bike-share]* *trips did you make?"* Respondents were asked to use their phone app or online account to retrieve the exact number of trips in the past 28 days. We estimate a negative binomial regression model to predict bike-share use frequency as our response variable is over dispersed. We consider the negative binomial regression in the following form.

$$Y_i \sim NB\,(\lambda_i, \varnothing) \tag{2}$$

$$\begin{aligned} log(\lambda_i) = & \beta_0 + \beta_1 City + \beta_2 Employment\ Status + \beta_3 College\ Education \\ & + \beta_4 Race + \beta_5 Student\ Status + \beta_6 Income\ Status + \beta_7 Gender \\ & + \beta_8 Age + \beta_9\ Having\ Kids + \beta_{10} Auto\ Ownership\ Status \\ & + \beta_{11} Like\ Bike\ Attitude + \beta_{12} Car\ Necessity\ Attitude \end{aligned} \tag{3}$$

Where $\varnothing$ is the overdispersion parameter that is constrained to be positive, β_0 is the mean rate, and all beta parameters represent the contribution of each corresponding predictor variable of their products.

Modeling Bike-share Use Purpose. The travel purpose models use data from both waves of the bike-share user survey. The dependent variable in these models is the trip frequency by bike-share for specific travel purposes, including commuting, going to the grocery, going to work-related purposes, going to restaurants and bars, going to other shopping purposes, going to friends and family, going to errands, and going for recreational purposes. The survey asked, *"How often do you take JUMP bike trips for the following purposes? (A trip is defined as going from one location to another (one-way)) -…"*. The response to these questions had five categories: "Never," "Less than one trip a month," "1-3 trips a month," "1-2 trips a week," "3-4 trips a week," and "5+ trips a week." We converted these responses into monthly bike-share trip frequency for a travel purpose for each individual by taking the middle point of the categories (0 for "Never," 1 for "Less than one trip a month," 2 for "1–3 trips a month," 6 for "1–2 trips a week," 14 for "3–4 trips a week," and 20 for "5+ trips a week"). We estimate a negative binomial regression model to predict bike-share use frequency for each purpose independently as our response variable is over dispersed. We used similar approach as shown in eq. (2) and eq. (3).

3.4. Analysis of impact of bike-share on travel behavior

We analyze the impact of bike-share on travel behavior in multiple ways. First, we calculate a "disruption index" that reflects an individual's change in the use of different modes as they incorporate bike-share into their travel patterns. In the bike-share user survey, we asked users how their use of different modes (i.e., car, carpool, transit, walk, bike, and ridehail) changed after they began using bike-share. We asked a similar question prospectively by asking how they would change their use of different modes in the event that bike-share stopped operating. We also asked them about their likely change in activity patterns, trip making, and car ownership status in the event that bike-share were to stop operating. We converted individual responses into binary categories (0 for no change and 1 for change in use of a mode) as described in Table 2. We call the binary variable for specific modes the mode-specific disruption index. We calculated an overall mode disruption index by summing mode-specific scores for each individual. We used a similar approach to calculate mode disruption indexes in the event of a bike-share shutdown, and for changes in activity patterns, trip making, and car ownership status in the event of a bike-share shutdown. We then summed mode-specific, activity pattern, trip making, and car ownership status disruption indexes to get an overall disruption index for each individual. These indexes give an indication of how bike-share affects travel making decisions.

We also created a measure of the individual's willingness to walk for a 15-min bike-share trip. Individuals can check the location of the dockless shared bikes in the surrounding area using their mobile phone app and based on the distance to the bike decide whether they want to book the bike or not. We assumed that individuals with fewer transportation options were willing to walk farther to get a bike for a long trip. Thus, an individual's willingness to walk to access the service provides an indication of the importance of the service to meet their travel needs and is likely to vary for different income, race, and car ownership groups. We create the willingness to walk score for each individual by converting their categorical responses into equal interval scores as shown in Table 2.

Table 2
Variables used to measure the travel behavior change due to bike-share.

Scale	Outcome Name	Outcome Details	Variable Type	Values
Individual				
	Change in mode use if the bike-share stopped	How do you think your travel would be affected in these ways if JUMP bike-share service suddenly stopped? – I would use public transit…/ drive/ personally owned bike, walk/ Uber/ Lyft/ carpool	Binary coding for responses (0/1)	The same amount (0), Changed (i.e., Much less often, Much more often, Somewhat less often, Somewhat more often) (1)
	Change in activity, trip, and car ownership if bike-share stopped	How likely is it that your travel would be affected if JUMP service suddenly stopped? – I would need to change the time of my activities/ cancel some of my trips/ buy a car	Binary coding for responses (0/1)	Not at all likely (0), Other (i.e., Somewhat likely and Very likely) (1)
	Change in mode use due to their use of bike-share	In general, since using JUMP, how have you changed how you…– Use public transit (train or bus)/ drive a car alone/carpool/ ride my personally owned bike/ walk/ ridehailing service (e.g., taxi, Uber, Lyft)	Binary coding for responses (0/1)	I have changed how I use it because of JUMP (1), Not changed due to bike-share (i.e., I did not use it before, and I do not use it now, I have changed how I use it but not because of JUMP, I have not changed how I use it) (0)
	Willingness to walk to access a bike for a 15-min trip	If you wanted to use JUMP for a 15 min ride, how long would you be willing to walk to get a bike?	Responses converted to equal interval scores	Up to 2 min (1), Up to 5 min (2), Up to 10 min (3), Up to 15 min (4), and >15 min (5)

3.5. 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 that it would bias our analysis. Studies show that the multiple imputation method is superior to listwise deletion for handling missing data (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 models on each dataset and pooled the results using the Rubin rule to make inferences (Rubin, 1987). This method assumes the multiple repeated parameter estimates are normally distributed (Heymans and Eekhout, 2019; Rubin, 1987).

3.6. Limitations

Because our recruiting method for the user survey included intercepting and asking bicyclists on personal bicycles if they had ever used the bike-share system, the sample of bike-share users is potentially biased towards 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.

The substitution questions in the individual-level analysis provide a better indicator of causal relationships than a cross-sectional analysis alone, in that they measure the possible change in a mode use in response to the appearance or disappearance of the bike-share system. However, this approach is not as robust as an approach that measures an individual's mode use before and after the introduction of bike-share (or before and after the elimination of bike-share) using an experimental design.

In the modeling of bike-share adoption and use frequency, we did not control for the shared bike availability on different block groups and surrounding the users' home, work, and/or school locations (in the dockless framework this variable may have some effect) using the home, work, and/or school locations of each individual that are beyond the scope of this study.

We also did not explore operational features that may restrict the availability of bikes to lower income groups (e.g., cost of access, lack of payment options, etc.) as these are not part of the study objective. Previous studies have already explored these features and we refer to those in our literature review and policy implications section.

Care should be taken in generalizing the results of this study to other contexts. The method used in this study can be applied in different study areas, but the results may differ based on socio-demographic, bike-share, built environment, and other city-specific characteristics.

4. Results and discussion

4.1. Do the different groups adopt the service at different rates?

To understand whether different groups adopt the service at different rates, we compare the user demographics of the bike-share users with the study area socio-demographics. As we can observe from Table 3, middle-income groups are overrepresented in the bike-share user base and the low-income group is underrepresented. Also, white individuals are overrepresented and Black and Hispanic residents are underrepresented in the bike-share user group. Non-auto owners are overrepresented in the bike-share user base. This result should be interpreted with caution as this study used an intercept method of collecting bike-share user data. It is difficult to assess the representativeness of the sample as we do not have data on the characteristics of the bike-share user population (since the bike-share operator did not provide this). These results are aligned with previous bike-share studies (Grasso et al., 2020; McNeil et al., 2018; Shaheen et al., 2014; Stromberg, 2015). Similarly, a large portion of our bike-share user sample is also middle income, and a very low portion is low income. This suggests that our

Table 3
Characteristics of household survey (HH) and bike-share user survey and the study area population overall and by city.

Variable		After Bike-share HH Survey	Bike-share User Survey	Davis	Sacramento	West Sacramento
Population		–	–	68,640	503,482	53,151
Response rate		10%	–			
Sample size	Wave 1	831	462			
	Wave 2		409			
Enrolled student			25%	51%	25%	28%
Races	White	78%	65%	63%	44%	63%
	Black	4%	4%	3%	14%	5%
	Hispanic	9%	13%	13%	28%	33%
	Asian	8%	18%	23%	19%	12%
Education status	College education	75%	76%	75%	34%	30%
	No college education	25%	24%	25%	66%	70%
Age	(median)	52	33	25.5	36.2	34.3
Gender	Woman	54%	41%	54%	51%	51%
Household income	Low Income	15%	20%	39%	39%	36%
	Middle Income ($50,000 to $150,000)	60%	57%	36%	44%	48%
	High Income (>150,000)	25%	23%	25%	17%	16%
Auto ownership	Non-auto owner	6%	14%	4%	4%	3%
Bike to work		–	–	17.5%	1.9%	1.4%
Population density		–	–	6703	5323	2511
Percent of City under bike-share		–	–	100%	27%	46%
Road density (mile per sqm)		–	–	66.19	57.19	44.24
Bike lane density (mile per sqm)		–	–	11.3	1.32	1
Point of interest density (per sqm)		–	–	38	15	7
Transit Systems		–	–	Bus and commuter rail	Bus, light rail, commuter rail	Bus

Source: (Data USA, 2019; GEOFABRIK, n.d.; OpenStreetMap, n.d.; US Census Bureau, 2021), Bike-share User Survey (2018 & 2019) and Household Survey (2019) described in the data collection section of this article.

sample has captured at least some of the demographic variability in the bike-share user population. We provide demographics statistics for the study area population and the sample to enable the reader to judge the representativeness of the sample themselves.

After comparing the bike-share user demographics collected from the survey with the study area, we modeled bike-share adoption and bike-share use frequency to understand whether bike-share use differs among different socio-demographic groups adjusting for other factors (i.e., travel-and-mode related attitudes, employment status, location of residences, and auto ownership).

As these are two different models on two different datasets, we compare the direction of the coefficients to understand whether there is a difference between different socio-demographics in terms of adoption and use frequency. The results of the models are shown in Table 4.

Our model results indicate that low-income users (household income less than $50,000 or personal income less than $25,000) are less likely to first try the bike-share service (although the variable is not significant at a 10% significance level, the sign and the magnitude of the effect indicate this variable may be relevant) but use the service more frequently when they do try it. Car ownership has a strong influence on both using bike-share and the frequency of use. Individuals living in zero-car households are more likely to adopt the service and use it at high frequency as illustrated by sizable differences in coefficients between auto owners and non-auto owners in Table 4.

Our results also show that women are less likely to initially adopt bike-share, and if adopted, their frequency of use is much lower compared to men (Table 4). A gradual decline can be observed in the adoption of bike-share with an increase in age. One thing to note is that only those aged 50 years and over show a greater frequency of use compared to other age groups; however, this group is significantly less likely to adopt the service compared to other age groups. We did not find any noticeable effect of race on bike-share adoption as well as on the frequency of use (Table 4).

Table 4
Models for bike-share use (adoption) and frequency.

Variables of the Model	Bike-Share Use (binary) (Data source: Household survey)		Bike-share Frequency (count) (Data source: Bike-share user survey)	
Number of observations	830*		870*	
Variables	Estimate	Std. Error	Estimate	Std. Error
Intercept	−4.863***	1.100	1.280***	0.482
City: Other	–	–	0.065	0.237
City: Sacramento	1.493***	0.560	0.309*	0.182
City: West Sacramento (Base = Davis)	1.848***	0.606	0.092	0.209
Employment Status (Base = Not employed)	0.824**	0.340	0.491***	0.179
College Education (Base = No College Education)	−0.045	0.310	−0.062	0.157
Low Income	−0.748	0.522	0.587***	0.213
Middle Income (Base = High Income)	−0.269	0.290	0.397***	0.146
People of color (Base = White)	−0.217	0.293	−0.034	0.118
Gender (Woman = 1, Other = 0)	−0.272	0.241	−0.385***	0.120
Student Status (Yes = 1, No = 0)	−0.012	0.529	0.456***	0.146
Age (30 to 40)	−0.433	0.375	0.091	0.168
Age (40 to 50)	0.564	0.356	0.143	0.206
Age (older than 50) (Base <30)	−1.077***	0.346	0.524**	0.240
Having Kids	−0.066	0.294	0.014	0.151
Non-auto owner (Base = auto-owner)	1.083*	0.571	0.662***	0.214
Like bike attitude	2.544***	0.750	0.100	0.319
Car necessity attitude	−0.571	0.570	−0.084	0.239
Average Model AIC**	521.6463		5971.547	

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

* We run multiple imputation model on 20 datasets where each dataset has this number of observations.

** Reported AIC is average across 20 models ran on 20 multiple imputation datasets.

These results both confirm and refute the findings of previous studies. Our results align with the findings of Winters et al. (2019) and Oates et al. (2017) showing that low-income users are more likely to use bike-share more. Our results differ from the study by Chen et al. (2020) based on user data from a Chinese dockless bike-share system showing that bike-share is popular among younger, more highly educated, and median-income groups; use frequency for different purposes mostly appeared to be independent of gender and income.

Our results provide an indication that initial adoption is an important barrier for low-income groups, but for those who try it, bike-share becomes a more frequent travel choice. One possible explanation for this result could be that frequent users with low incomes are more likely to have subsidized user passes and thus use it frequently. However, our data shows that the majority of low-income frequent users do not have a subsidized pass (see Table 1), rather they "pay as they go" like all other users (at least they self-report that they do so).

Findings from the attitude analysis strengthen the argument that an individual being in a transport-disadvantaged group is a stronger predictor of use frequency than adoption, which is dependent on several factors apart from being a member of a transport-disadvantaged group. The like-bike attitude significantly positively influences adoption with a sizeable effect size. This is aligned with previous studies showing that individuals' attitudes influence their mode choice decision (Handy et al., 2010b; Kitamura et al., 1997; Kroesen et al., 2017). However, none of the attitude variables were significant in the bike-share frequency model and their estimates were small indicating that frequent use of the service may not be influenced by travel-and-mode-related attitudes but rather by other factors such as the importance of the service in fulfilling their regular travel needs, a point addressed in the next section.

Our models show that both bike-share adoption and use frequency vary significantly across cities with varying bike infrastructure and bicycling cultures. Individuals living in Sacramento and West Sacramento are significantly more likely to adopt bike-share than Davis residents. Individuals living in Sacramento are also significantly more likely to use the bike-share frequently than individuals living in Davis. On one hand, this finding is surprising, given that Davis has a high density of bike infrastructure compared to the other two cities as shown in Fig. 1 and Table 3, and that previous studies have found that having more bike lanes is positively associated with bike-share use (Alcorn and Jiao, 2019; Buck and Buehler, 2012; Lin et al., 2020; Shen et al., 2018). On the other hand, Davis has among the highest use of personal bicycling in the U.S. Our result suggests that people living in a well-established bicycling community may see less need for the bike-share service since they are accustomed to using their own bikes already. Bike-share may thus be more important as a strategy for boosting bicycling in communities where residents have given less thought to this mode of transportation.

4.2. How do frequency and purpose of use vary across groups?

Analysis of the use of bike-share by transport-disadvantaged groups to perform a variety of travel activities can give a better picture of the equity implication of the service. Apart from frequent commuting trips, individuals have a variety of other infrequent but regular travel needs such as going to the grocery store, other shopping, doing errands, going to a restaurant, going to friends and family, and going for recreational tours, etc. A car can be a convenient option to meet all these travel needs except that it is unaffordable to many. However, access to an electric bike can also assist individuals in making longer commute trips as well making grocery trips that require the carrying of goods. To understand

Table 5
Results of bike-share use purpose models (only showing the coefficient estimates and the significance).

Variables	Commute	Work related	Grocery	Other shopping	Errands	Restaurant	Friends and family	Recreational
Number of observations*	870	870	870	870	870	870	870	870
(Intercept)	1.006	1.239*	−0.626	−0.349	−0.124	0.953*	0.763	−0.381
City: Other** (Base = Davis)	−0.418	0.088	0.387	0.075	0.313	0.148	0.349	0.838***
City: Sacramento (Base = Davis)	−0.101	0.069	0.620**	0.727***	0.709***	0.505***	0.662**	0.438*
City: West Sacramento (Base = Davis)	−0.174	−0.212	0.311	0.517**	0.347	0.090	0.477	0.452
Employed (dummy)	0.844***	0.983***	−0.281	−0.675***	−0.369*	−0.094	−0.215	−0.216
College Education (Dummy)	−0.241	−0.335	0.086	−0.150	−0.120	−0.117	−0.390**	−0.491**
Income: Low (Base = High Income)	0.578*	0.091	0.904**	0.470*	−0.189	−0.041	−0.074	0.552*
Income: Middle (Base = High Income)	0.260	−0.128	0.298	0.236	−0.027	−0.067	0.035	0.187
Race: People of color (Base = White)	0.157	0.140	0.570***	0.334**	0.468***	−0.082	−0.028	0.091
Gender: (Base = Male)	−0.286*	−0.426***	−0.111	−0.072	0.038	−0.208*	−0.164	0.000
Student (Dummy)	0.373*	0.243	0.336*	0.280	0.221	0.239*	0.131	0.055
Age: 30 to 40 (Base = <30)	−0.076	−0.016	−0.304	−0.415**	−0.200	−0.182	−0.369*	−0.087
Age: 40 to 50 (Base = <30)	−0.225	0.232	−0.124	−0.291	−0.178	−0.170	−0.324	−0.602*
Age: Older than 50 (Base = <30)	0.022	0.288	0.443	0.203	−0.186	−0.192	−0.836***	0.358
Having Kids (Dummy)	0.226	0.112	−0.012	−0.045	−0.013	−0.063	−0.300	−0.143
Non-auto owner (Dummy)	0.283	0.030	0.515**	0.314	0.707***	0.382**	0.169	0.077
Like bike attitude	−0.638	−0.963*	0.498	0.855*	1.278**	0.326	0.672	0.974*
Car necessity attitude	0.240	−0.699**	−0.972***	−0.577**	−0.775***	−0.045	−1.059***	0.144
Average Model AIC***	3988.602	3026.67	2525.108	2613.41	3465.763	4099.55	2799.765	3091.442

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
* We run multiple imputation model on 20 datasets where each dataset contains 870 observations.
** Individuals living outside the bike-share boundary use the service and participated in the bike-share user survey and we code their city as other.
*** Reported AIC is average across 20 models ran on 20 multiple imputation datasets.

the degree to which transport-disadvantaged groups use bike-share for different travel purposes, we model bike-share use frequency for different utilitarian and recreational purposes.

The results of these models are shown in Table 5. Lower-income users are significantly more likely to use the service for both utilitarian and recreational purposes. The significant positive coefficients from the models show that low-income users are more likely than other groups to use bike-share for commuting, doing groceries, shopping, and recreational purpose, assuming all other predictors (i.e., travel-and-mode related attitudes, age, gender, race, employment status, location of residences, and auto ownership) are held constant. Non-auto owners are more likely than auto owners to use the service for commuting, doing groceries, errands, and going to restaurant purposes.

Although Davis residents are less likely to adopt and use bike-share frequently, they are more likely to use the service for commuting purposes. This is aligned with the bicycling culture of Davis where a large portion of individuals bike to work or school as mentioned earlier. However, for all the other utilitarian and recreational purposes, Davis residents are less likely to use bike-share compared to other locations. This is not aligned with the bicycling context of Davis as people living in Davis are also more likely to use bicycles for other utilitarian purposes. To understand why residents of Davis are not using bike-share at greater rates for non-work and non-school utilitarian travel requires further study. Except for commuting and work-related purposes, residents of Sacramento are more likely to use bike-share for the other selected travel purpose categories. West Sacramento residents are significantly more likely to use the service frequently for shopping purposes compared to Davis residents. These findings further bolster the earlier findings that bike-share is likely to positively influence bicycling in areas lacking bike infrastructure and use (Guo et al., 2022; Pucher et al., 2011).

From this analysis, it is evident that low-income users, people of color, and non-auto owners are more likely to use the bike-share service frequently for most of the utilitarian purposes analyzed. This finding signals the contribution of bike-share systems to transportation equity: low-income users, people of color, and non-auto owners are using the service to connect to income opportunities and/or to fulfill regular travel needs. This finding indicates that although the low-income segment of the population adopts the service at a lower rate, a result also found in previous studies (Grasso et al., 2020; McNeil et al., 2018; Shaheen et al., 2014), bike-share is an important mode of travel for this segment for a variety of utilitarian as well as recreational travel purposes. The potential benefits of bike-share, a lower cost mode than driving, make the low rate of adoption by people with low incomes that much more of an equity concern.

The effect of race (white vs. people of color) on bike-share use purpose is also notable. Although several studies show that white individuals are more likely to adopt the service (Grasso et al., 2020; McNeil et al., 2018; Shaheen et al., 2014), our model results show that they are less likely to use the service for various utilitarian purposes compared to people of color. Low-income individuals, non-auto owners, and people of color are more likely to use electric bike-share services for grocery and other shopping activities that may require the carrying of goods while biking. The battery-electric capability of the service as well as the design of the bikes with a basket in front may have facilitated the use of bike-share for these purposes.

The analysis shows a sizable difference between auto owners and non-auto owners in the use of bike-share for different travel purposes. Non-auto owners are more likely to use the service for several utilitarian purposes and recreational purposes compared to auto owners. Bike-share may be enabling them to remain car free by taking care of needs that would otherwise require a car, but more research is needed to understand this possibility.

4.3. How does the impact of bike-share on travel behavior vary across groups?

We analyzed this impact of bike-share on travel behavior both retrospectively (i.e., change in the use of different modes following the adoption of bike-share) and prospectively (i.e., probable change in the use of different modes in the event of a bike-share shut down) using the disruption index scores. In this portion of the analysis, we define two low-income groups – low-income persons who are not students and low-income students - because our sample contains a considerable number of

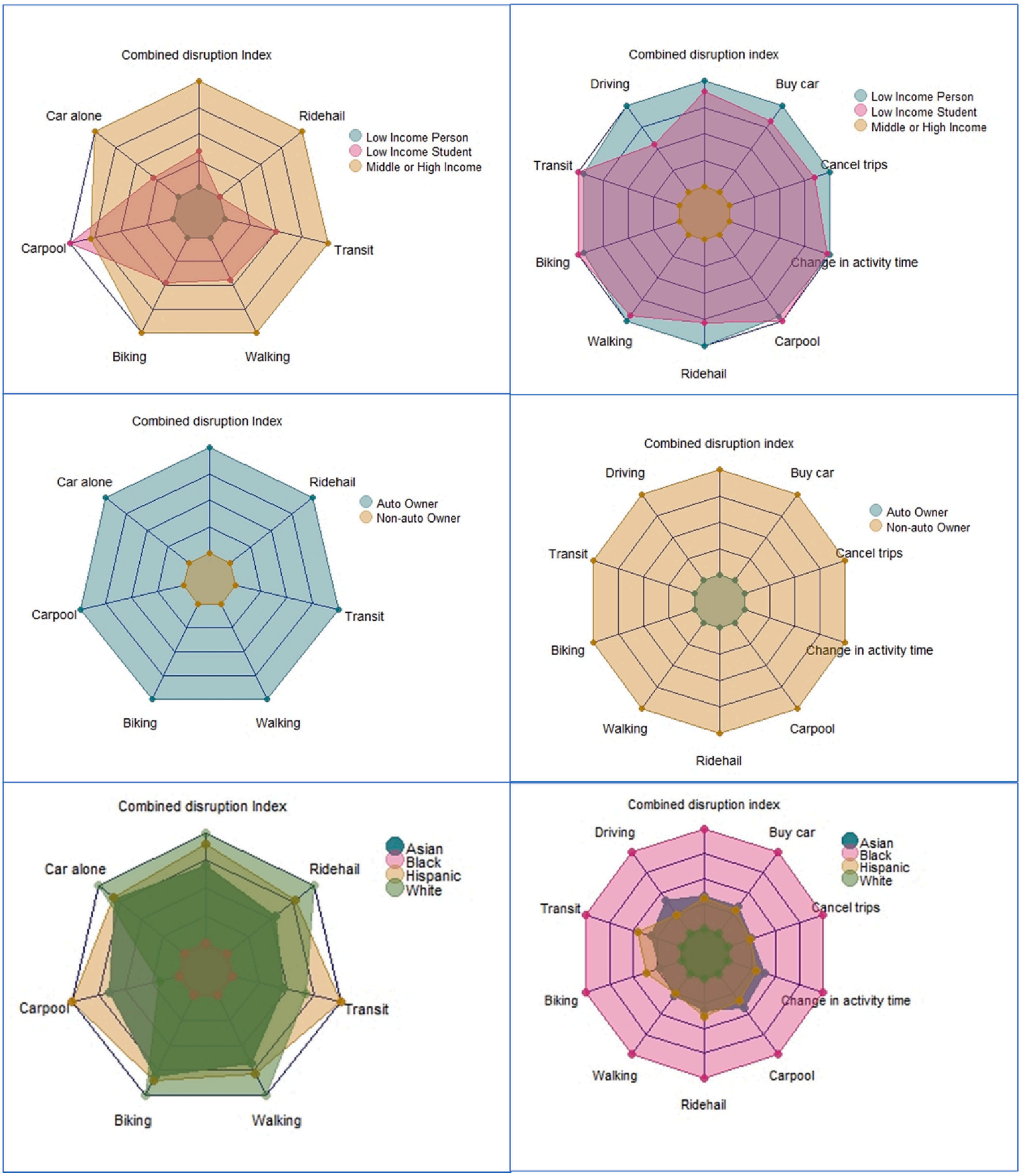

Fig. 2. Mode wise travel disruption index value for different user groups following the adoption of bike-share (left panel) and if the bike-share stopped service (right panel).

students (especially from the University of California, Davis), many of whom are low-income and who tend to have distinctive travel patterns. The independent sample *t*-test shows that all of the combined disruption index scores are significantly different between income groups (i.e., low-income person (0.779) vs. low-income student (1.10) and low-income person (0.779) vs. middle or high income (1.72)), between auto-ownership groups (auto owner (2.02) vs. non-auto owner (0.578)), and between race groups (people of color (combined mean score of Black, Asian, and Hispanic) (1.04) vs. white (1.92)) at a 1% significance level.

Comparisons of the mode-wise travel disruption indexes are shown in Fig. 2. The radar plots show the relative position of each group with respect to each variable. For a given variable (e.g., mode), if the color of a group extends towards the border of the radar, that indicates that the group has the highest value for that variable, and if the color of a group is not visible for a variable and appears at the center with a dot, that indicates that the group has the lowest value for that variable.

In most cases, a higher proportion of middle and high-income individuals, auto owners, and white individuals report a change in their use of different modes due to their adoption of bike-share, particularly their use of driving, biking, walking, and ride-hail. As the index values for each mode are derived from the binary coding of the survey question, they can be interpreted as the percentage of individuals in a group who changed that mode due to bike-share. The results suggest that bike-share may have influenced middle- and high-income users to become more multi-modal. The lower index value for low-income individuals, people of color (especially Black people), and non-auto-owner users may stem from the fact that they tend already to be multimodal travelers.

We also asked how likely bike-share users would be to change their use of other modes, how likely they would adjust their travel in other ways (i.e., change activity times or cancel trips), and whether their car ownership would change if the bike-share were to shut down. The difference in the disruption index in the case of a shutdown compared to the case of bike share adoption is sizable (Fig. 2). The independent sample t-test shows that all the combined disruption index scores are significantly different between income groups (i.e., low-income person (6.95) vs. low-income student (6.68) and low-income person (6.95) vs. middle or high income (4.19)), between race groups (people of color (6.43) vs. white (3.55)), and between auto-ownership groups (auto owner (3.30) vs. non-auto owner (7.82)) at a 1% significance level. Lower-income users are more likely to report a change in driving, using transit, walking, biking, use of carpool, and use of ride-hailing in the event of a bike-share shutdown. Also, a higher portion of low-income individuals report a likely change in their activity patterns as well as a high probability of canceling some trips if the bike-share were to shut down. Higher percentages of low-income individuals and non-auto owners report they would need to buy a car in the event of a bike-share shut-down. Their higher disruption index value for each mode category in the event of bike-share shutdown compared to the retrospective condition might partly be due to the use of bike-share for new trips. Rather than giving up these new trips in the event of a bike-share shutdown, these individuals might prefer to find other ways to make them.

Even though these responses are prospective (and thus highly uncertain), the higher percentage of low-income individuals and non-auto owners with the intention to change travel behavior in the event of a bike-share service shutdown suggests that bike-share is providing a vital service to these groups. Bike-share also has some influence, though minor, on an individual's car ownership pattern: a higher proportion of low-income individuals and zero-car households report that they would likely need to buy a car if the bike-share were to shut down. These results are also aligned with the previous section that showed that low-income individuals, people of color, and zero-car owners are more likely to use electric bike-share for various trip purposes. These results thus suggest that in the event of an electric bike-share shut down, these groups are more likely than others to change their travel behavior, mode use, and car ownership.

We also analyzed how long an individual is willing to walk for a fifteen-minute bike-share trip, as a willingness to walk farther might indicate fewer available alternatives and thus a greater importance of bike-share in meeting an individual's daily needs. Both low-income individuals (mean willingness score of 3.06 vs. 2.29 for middle or high income), people of color (mean willingness score of 2.89 vs. 2.09 for white), and non-auto-owners (mean willingness score of 3.35 vs. 1.98 for auto owners) are more likely to walk more to get a shared bike for a fifteen-minute bike-share trip. The faster speeds enabled by electric bikes means that users can travel farther in fifteen minutes than with conventional bike-share, potentially making the service that much more useful – and worth a longer walk. However, trip-level data is necessary to validate this point for different user groups. The Independent sample *t*-tests show that all the scores are significantly different between income groups, between race groups, and between auto-ownership groups at a 1% significance level.

5. Conclusions and policy implications

Our analysis for the Sacramento bike-share system shows that white and middle-income users are potentially over-represented in the bike-share user base and low-income users are potentially under-represented; non-auto owners are also potentially over-represented in the user base. These findings are consistent with previous studies (Grasso et al., 2020; Shaheen et al., 2014). The analysis of use frequency shows that both low-income individuals and non-auto owners are using bike-share at a much higher frequency compared to others. These findings are aligned with most previous studies (Oates et al., 2017; Winters et al., 2019). Analysis of trip purposes shows that the purposes for which bike-share is used vary across groups. Low-income individuals, non-auto-owners, and people of color are using the service for many utilitarian and recreational trip purposes at a higher rate than others. All users change their use of other modes when they incorporate bike-share into their travel patterns, but low-income individuals, people of color (especially Black people as seen in Fig. 2), and non-auto owners are more likely to be more severely impacted (in the form of changing modes, canceling trips, adjusting activity time, and buying a car) if the service were to stop. These findings are evidence of the importance of bike-share as a travel mode for transport-disadvantaged groups, though they are under-represented in the user base. We find that individuals living in communities with a strong bicycling culture are less likely to adopt bike-share but more likely to use it for commuting. This finding may be unique to the study area as Davis has a very high rate of bicycling by US standards making it difficult to generalize the finding.

The major strength of this study is the depth of its exploration of bike share use. Previous studies have mostly been limited to examinations of the adoption and the use of the service by different socio-demographic groups. This study goes beyond those questions to explore the different purposes for which the service is being used, the impact of the bike-share on users' travel patterns, and the potential effect on travel patterns and vehicle ownership if the service were to suddenly stop operating. Our analysis of these aspects of bike share use for different socio-demographic groups provides a deeper understanding of bike-share equity.

Our findings suggest that bike-share can enhance equity while also addressing sustainability. 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-share, leading to reductions in GHGs, air pollution, congestion, noise pollution, and an increase in physical activity. A higher portion of low-income individuals, people of color, and non-auto owners expressing the likelihood that they would increase driving as well as buy a car in the event of a bike-share shut down reflects the extent to which bike-share is substituting for driving, with benefits for equity as well as sustainability.

Our study adds new insights into the use of the service for different utilitarian and recreational purposes. These findings are important for developing sustainable transport policies for two reasons. First, if cities can increase the share of low-income individuals, people of color, and non-auto-owners in the bike-share user base, the sustainability benefits of the service will increase. Second, increasing the use of the service among low-income individuals, people of color, and non-auto owners may enable them to connect to employment and other opportunities without needing to own or maintain a car. To increase the adoption of the service by transport-disadvantaged groups, cities can adopt policies that require better availability in areas where low-income individuals and people of color tend to reside. Cities should 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). Making it possible to use the service without a smartphone and credit card would also expand access to transport-disadvantaged groups.

Future research should also explore more directly the link between policies and equity outcomes. This will require evaluations of actual real-world policies through surveys and data collection before and after policy implementation. Data from GBFS and Mobility Data Specification can provide important insights into the spatial patterns of bike-share use, analysis that can help cities establish rules about bike distribution to ensure equitable access. In the wake of COVID-19, when bike-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 to increase transportation equity.

Author contributions

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

Data availability

Data will be made available on request.

Acknowledgements

The collection of the data used in this study was funded by the National Center for Sustainable Transportation and the California State Transportation Research Program. Thanks to the Sacramento Area Council of Governments for assistance and to Dr. Jesus Barajas of the University of California, Davis for providing valuable suggestions.

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