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What factors influence the adoption and use of dockless electric bike-share? A case study from the Sacramento region

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ABSTRACT

Now that dockless electric bike-share systems have become a fixture in major cities in the U.S., it is important to understand why someone chooses to use the service. Beyond socio-demographics, factors such as mode-related attitudes, the social environment, and the availability of the service may influence both its adoption and frequency of use. In this study, we modeled dockless electric bike-share adoption and use frequency using data collected from a household survey and a bike-share user survey from the Sacramento region. We used integrated choice and latent variable models to understand the influence of attitudes on electric bike-share adoption and use frequency. We developed three latent variables – bike affinity, car necessity, and bike social environment – using responses to eleven statements. Our models show that apart from socio-demographics, attitudes related to bike affinity and bike social environments significantly and positively influence bike-share adoption with a large effect size, whereas the car necessity attitude significantly and negatively influences the use frequency with a large effect size. Individuals with low incomes are less likely to adopt the bike-share service. The availability of electric bike-share in key locations (home and/or work and/or school) where an individual frequently goes significantly and positively influences adoption with a large effect size but does not influence use frequency. Findings from this study can inform the dockless electric bike-share policies of cities as well as the rebalancing strategies of service providers.

1. Introduction

Cities around the world have implemented bike-share systems in the last decade, and these systems have attracted substantial ridership, including in the U.S. (National Association of City Transportation Officials 2020). The most recent systems offer dockless electric-assisted bicycles (e-bikes) rather than the dock-based conventional bicycles offered by the first bike-share systems. These new services have the potential to attract even more riders, given the greater speed and ease of travel of e-bikes and the flexibility in pick-up and drop-off locations of a dockless system. Bike-share operators adopted electric technology to improve the riding experience for

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existing users as well as attract new segments of users (Li et al. 2024; Treviño 2019). These systems are less likely to be affected by bad weather and more capable of competing with cars, as well as transit and ridesharing services by facilitating longer trips in comparison to traditional bikes (Campbell et al., 2016; Mohiuddin 2021; Mohiuddin et al. 2024; Yang et al. 2024). Dockless electric systems are also expanding rapidly across the U.S.: in 2023, people took 6.7 million trips on dockless electric bikes, a nearly 50 % increase from 4.5 million trips in 2022 (2023). Beyond ridership levels, however, little is known so far about the individual use of these dockless electric systems, particularly factors influencing an individual's adoption and frequency of using this service. Now that dockless electric bike-share systems have become a fixture in major cities in the U.S., understanding factors influencing the adoption and continued use of bike-share will be important for the planning of sustainable transportation systems.

A recent review of research on dockless bike-share systems highlights the need for new research that goes beyond socio-demographic characteristics to explore how attitudes, as well as service distribution, influence the dockless bike-share system use (Chen, van Lierop, and Ettema 2020a). Research so far on the users and non-users of bike-share mainly focuses on socio-demographic characteristics, although studies have found attitudes toward travel modes to be an important determinant of mode choice more generally (e.g.; Kitamura, Mokhtarian, and Laidet 1997). Some studies of bicycling have included attitudes such as pro-bike attitudes and concerns about safety, but these studies have not fully explored the role of attitudes in the electric bike-share adoption decision. The distribution of the dockless service to different population segments can also be an important determinant of bike-share adoption and use frequency. Existing research shows that dockless bike-share systems can provide communities with increased access to bikes, but not all segments of a community have equal access due to biased distribution policies and rebalancing systems (Hirsch et al. 2019). Exploring all these factors together will provide a richer understanding of an individual's adoption and use decisions.

This study addresses the following research question: *"How do socio-demographic characteristics, latent attitudes towards modes and the social environment, and the availability of dockless electric bike-share services influence the adoption and use frequency of those services?"* We use a combination of two datasets: (1) a household survey of both users and non-users after the introduction of a bike-share system into three cities in the Sacramento region, and (2) a user survey collected from users of that same bike-share system. We estimated integrated choice and latent variable (ICLV) models to determine the influence of latent attitudes along with socio-demographic characteristics on the adoption and use frequency decisions of individuals in the study region. The model results provide important insights into the factors that influence the adoption and use frequency of dockless electric bike-share.

2. Literature review

Individual-level variables such as socio-demographic characteristics can play a role in the individual decision to adopt a bike-share service. Because studies show socio-demographic factors influence bicycling (Buehler and Handy 2008; Geus et al. 2008; Handy, Xing, and Buehler 2010; Willis, Manaugh, and El-Geneidy 2015), it is reasonable to expect that such factors influence the use of bike-share. Studies have shown that socio-demographics such as income, race, age, and education level are indeed associated with bike-share adoption (Shaheen et al. 2011; Shaheen et al. 2014; Tang, Pan, and Shen 2011). In addition, a study found no noticeable difference between the socio-demographic characteristics of electric bike-share and conventional bike-share users (Campbell et al. 2016). However, the effect of these factors is likely to vary by context, for example, Chinese bike-share systems compared to those in the U.S. and Western Europe.

Beyond the fact that one group uses electric bike-share and the other does not, it is possible that users are different from non-users in terms of their travel patterns, as observed in the case of users and non-users of ridehail services (Clewlow and Mishra, 2017; Mitra, Bae, and Ritchie 2019; Sikder 2019; Smith 2016) and carshare (del Alonso-Almeida, 2019; Hoerler et al. 2020; Hyun et al. 2021). It is also possible that users are considerably different from non-users in terms of travel-and-mode-related latent attitudes. Previous research on the users and non-users of shared micromobility (i.e., bike-share and scooter-share) has mainly focused on differences in socio-demographic characteristics, although some studies have also examined differences in attitudes regarding bicycling, environment, travel flexibility, safety, comfort, and convenience of micromobility services (Blazanin et al. 2022; Chen et al., 2020b; Reck and Axhausen 2021). These studies have not fully explored the role of latent attitudes toward different modes, which other studies have found to be an important determinant of mode choice (e.g., Handy, Xing, and Buehler 2010; Kitamura, Mokhtarian, and Laidet 1997; Kroesen, Handy, and Chorus 2017). Apart from mode-related attitudes, the social environment surrounding the individual can also be an important factor in mode choice (Phithakkitnukoon et al. 2017; Pike and Lubell 2018); social influence can also be an important predictor of the adoption of new technologies (Kim and Park 2011; Wang, Li, and Xiao 2019).

A large number of studies that have focused on stated intentions to use the bike-share and scooter-share system (rather than actual use) have analyzed the role of attitudes. The majority of those studies are based on the theory of planned behavior (TPB), which states that a person's intention to perform a behavior is a strong predictor of actual behavior (Ajzen 1991). Studies employing the TPB as their theoretical framework have confirmed that attitudes are an important determinant of intention to use bike-share. Hazen et al. (2015) used the Technology Acceptance Model to understand an individual's intention to adopt a station-based public bike-share system in Beijing, China, and found that perceived convenience, quality, and value tend to predict more than 50 % of the variance in bike-share adoption intention. Another study by Yu et al. (2018) showed that perceived usefulness and ease of use have a positive impact on a consumer's intention to use commercial bike-share services. Zhu et al. (2020) explored the effect of environmental concern on bike-share adoption intention and found that environmental concern is positively associated with attitude, subjective norm, and perceived behavioral control and that all these variables positively influence bike-share adoption intention (Zhu et al., 2020). Kim and Kim (2020) studied the factors that influence the intention to continue to use the bike-share and found that perceived value and trust in the service have a significant influence on consumer's intention to continue to use bike-share (Kim and Kim 2020).

Current research on the influence of attitudes on actual electric bike-share adoption and use is limited. Studies show that attitudes towards bicycling are correlated with bicycling behavior in general (e.g., Handy, Xing, and Buehler 2010) and that an individual's attitudes have an important influence on the intention to use different modes (Ashok, Dillon, and Yuan 2002; Eriksson and Forward 2011). Because bike-share services provide an alternative way to bicycle, the factors affecting bicycling might also affect the adoption of bike-share. In addition, attitudes may play an important role in the case of electric bikes due to their added convenience and utility. At least one study shows that a pro-bike attitude is positively associated with bike-share adoption (Chen, van Lierop, and Ettema 2020b). Another study shows that safety concerns, time consciousness, and green lifestyle propensity latent attitudes significantly influence the adoption and continued use of e-scooters and bike-share (Blazanin et al. 2022). Attitudes towards other modes (such as personal cars) are also associated with bicycling behavior (Geus et al. 2008; Willis et al. 2015) and may influence bike-share adoption. In addition, studies show that the social environment plays an important role in influencing bicycling motivation (Handy, Xing, and Buehler 2010) and bicycling behavior (Geus et al. 2008; Willis et al. 2015) and could also influence bike-share adoption. However, the existing literature on bike-share adoption, especially the adoption of dockless electric bike-share, does not include a study of the influence of mode-related attitudes and social environment.

Studies exploring factors influencing the actual adoption of micromobility services (including both bike-share and scooter-share) are summarized in Table 1. Most studies consider socio-demographic characteristics, but few explore the role of latent attitudes toward different modes (e.g., attitude towards bicycling, environment, safety, etc.). We have marked those studies with an (*) asterisk sign to differentiate them from studies that considered only socio-demographic characteristics.

An individual's choice to use dockless bike-share may be influenced not only by socio-demographic characteristics, attitudes, and the social environment but also by the degree of availability of the service itself. In particular, dockless bike-share has the potential to considerably reduce the access barriers associated with station-based systems because the bikes are free-floating and can be available in many more locations (Qian, Jaller, and Niemeier 2020). Nonetheless, the degree of availability can vary with dockless systems compared to station-based systems. One study found that bike-share operators, in an effort to boost demand, tended to locate stations near wealthy neighborhoods (Duran-Rodas et al. 2021). Another found more dockless bike availability in higher median income and more college-educated neighborhoods (Mooney et al. 2019). The business strategies of bike-share companies often result in bike

Table 1
Selected studies of micromobility adoption and the factors considered.

Geography	Study Area	Authors	Factors Considered
North America	Austin, USA	(Blazanin et al. 2022)*	Both socio-demographics and attitudes such as safety concerns, time consciousness, and green lifestyle propensity latent attitudes Jointly modeled adoption and use frequency of e-scooter sharing and bike-sharing
	Boston, USA	(Franckle et al. 2020)	Socio-demographics and regular mode use patterns to understand bike-share use
	Baltimore, USA	(Grasso, Barnes, and Chavis 2020)	Socio-demographics and barriers to bike-share adoption aspect among users and non-users
	Rosslyn, USA	(James et al. 2019)	Perception regarding the safety around riders of e-scooters, and experiences of sidewalks blocked by e-scooters aspects
	Tempe, USA	(Sanders, Branion-Calles, and Nelson 2020)	Socio-demographics and barriers to e-scooter adoption aspect among users and non-users
	Texas, USA	(Kellstedt et al. 2019)	Focus group discussion with both user and non-user groups to understand the barriers to the adoption of dockless bike-share
	Washington D.C., USA	(Buck et al. 2013)	Developed profile of user demographics from data collected from the regional household survey and bike-share user survey
Europe	Denmark	(Kjærup et al., 2021)	Collected data from user and non-user perspectives through three distinct data collection techniques: interviews with e-scooter riders, observations of e-scooter riders in urban environments, and a preliminary analysis of social media comments
	Switzerland	(Reck and Axhausen 2021)*	Both socio-demographics and attitudes, such as priorities for environment, travel time, and travel flexibility. Jointly modeled adoption and use frequency of shared micromobility
	Denmark and Sweden	(Breengaard, Henriksson, and Wallsten 2021)	Using the focus group method, this study finds that the non-use of shared bicycling in Scandinavia can be described by three statements: "I have my own bicycle," "I travel with kids," and "I don't feel safe."
	Greece	(Nikiforiadis et al. 2021)	Safety, comfort, potential improvements, and traffic regulations aspects of e-scooters from the Greek context
	Germany	(Petzoldt et al. 2021)	Knowledge of the rules of using shared e-scooters from the German context
Asia and Oceania	Xi'an, China	(Wang, Dong, and Ma 2024)*	Includes attitudes, social norms, and perceived behavioral control along with socio-demographics Joint modeling of adoption and use intensity of bike-share for commuting and errands using structural equation modeling
	Beijing, China	(Chen et al., 2020b)*	Both socio-demographics and attitudes, such as pro-bike attitudes, environmental concerns to understand bike-share adoption and use
	New Zealand	(Fitt and Curl 2020)	Socio-demographics to understand the e-scooters
	New Zealand	(Fitt and Curl, 2019)	Attitude regarding environment suitable for e-scooters
	Singapore	(Derrick 2020)	Attitudes towards the safety of e-scooters and attitudes towards banning e-scooters

Note:
[*] Studies that include both attitudes and demographics.

availability skewed towards certain customer groups. Unlike station-based systems, with dockless systems, the distribution of shared bikes can lead to the availability of bikes in very close proximity to home and work locations for more potential users. The finding from marketing studies that product exposure influences adoption (Blechar, Constantiou, and Damsgaard 2005) suggests that convenient availability of shared dockless bikes is likely to influence adoption decisions through such an exposure effect, in addition to the availability effect on usage rates. The analysis of factors affecting dockless bike-share adoption can thus be misleading if the analysis does not control for shared bike availability.

This study makes three unique contributions to current literature. First, our study is the first to examine the influence of the perceived social environment toward bicycling on an individual's adoption and use of dockless electric bike-share. Another important attitudinal factor we include is the attitude that a car is necessary; this factor is particularly important to consider in this study, given the car-dominated culture in the United States. We also include pro-bicycling attitude, confirmed in previous studies, as a potential explanatory factor. Second, we examine the influence of the availability of shared dockless bikes on adoption and usage. The dockless system's visibility and availability likely differ from those of the station-based system, which may lead to different adoption and use frequency levels. A variable that measures exposure can be an important factor affecting the adoption and usage decision for dockless electric bike-share services. Third, our use of the ICLV method provides important insights into the direct effect of demographic variables and isolates those direct effects from the indirect effects of demographic variables through the latent attitude variables. This is important from a policy standpoint as leaving out the attitude variables may result in the overestimation of the effects of demographic variables on dockless bike-share adoption and use and, as a result, bias the design of policies.

3. Data and methodology

This study explores the influence of socio-demographic characteristics, mode-related attitudes, perceived social environment towards bicycling, and bike availability on the adoption and frequency of use of bike-share services in different settings. JUMP operated the bike-share system in the greater Sacramento region and provided dockless, electric-assisted bikes (prior to the sale of JUMP to Lime and prior to the COVID-19 pandemic). We use survey data from the cities of Sacramento, West Sacramento, and Davis collected after the launch of the bike-share system in the Sacramento region.

3.1. Study area context

The focus of this study is the JUMP-operated electric bike-share service that launched in the greater Sacramento region in the summer of 2018. By May 2019, almost 1,000 e-bikes were available in the cities of Sacramento, West Sacramento, and Davis. The service also deployed 100 e-scooters in Sacramento and West Sacramento; however, bike-share use was dominant. The service covered an area of approximately 50 square miles, though the service area was not contiguous (see Fig. 1). Davis is a major university town, separated from West Sacramento by about 10 miles. These cities differ in their bicycling cultures and the quality of their bike infrastructure. Davis, in particular, is well known for its extensive bicycle network and long-standing bicycle culture (Buehler and Handy 2008). Interest in bicycling and development of supporting infrastructure in the other two cities is more recent. Bike infrastructure distribution is shown in green in Fig. 1. 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. The selected cities also differ in terms of socio-demographic characteristics, road and bicycling infrastructure density, and population density.

3.2. Data collection

The data used in this study were collected as part of a coordinated research effort on the topic of bike-share, spanning a timeline from 2016 to 2019: see Fig. 2. Two types of surveys were conducted: household surveys and surveys of JUMP bike-share users. Two surveys of each type were conducted (for a total of four surveys), and all data were collected prior to the COVID-19 pandemic. There is substantial overlap on many data elements across the two types of surveys, e.g., socio-demographics, attitudinal scales, etc.

The two household surveys were conducted in Spring 2016 and May 2019, respectively. The timing was selected in anticipation of the JUMP introduction to collect "before" and "after" data from the general population, using geographically stratified address-based random samples. In addition to addresses from the service areas in the three cities, addresses were generated for the South Natomas area (a neighborhood in Sacramento, not in the service area) to yield a type of "control sample.".

In contrast, the user survey was a two-wave longitudinal survey (with some panel refresh) of JUMP bike-share users in October 2018 and May 2019. Participants in both waves were recruited through interception at key locations and by fliers with the survey URL and QR code taped to e-bike seats. In addition, for the initial wave 1 recruitment, JUMP ran Facebook advertisements on our behalf (targeted by zip code). The research team based the field recruitment strategy on maximizing the number of users intercepted while at the same time 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.

Finally, because the second household and user surveys were conducted in parallel in May 2019, respondents recruited for the household survey who were identified as JUMP users were given the option of being re-routed to the user survey. This allowed us to identify a sub-sample of users generated through random sampling (versus the "choice-based" sampling described above). (See (Fitch, Mohiuddin, and Handy 2021) for additional survey design details.) For the purposes of this study, we use data from the two May 2019 surveys (i.e., the "after" household survey, and the Wave 2 user survey).

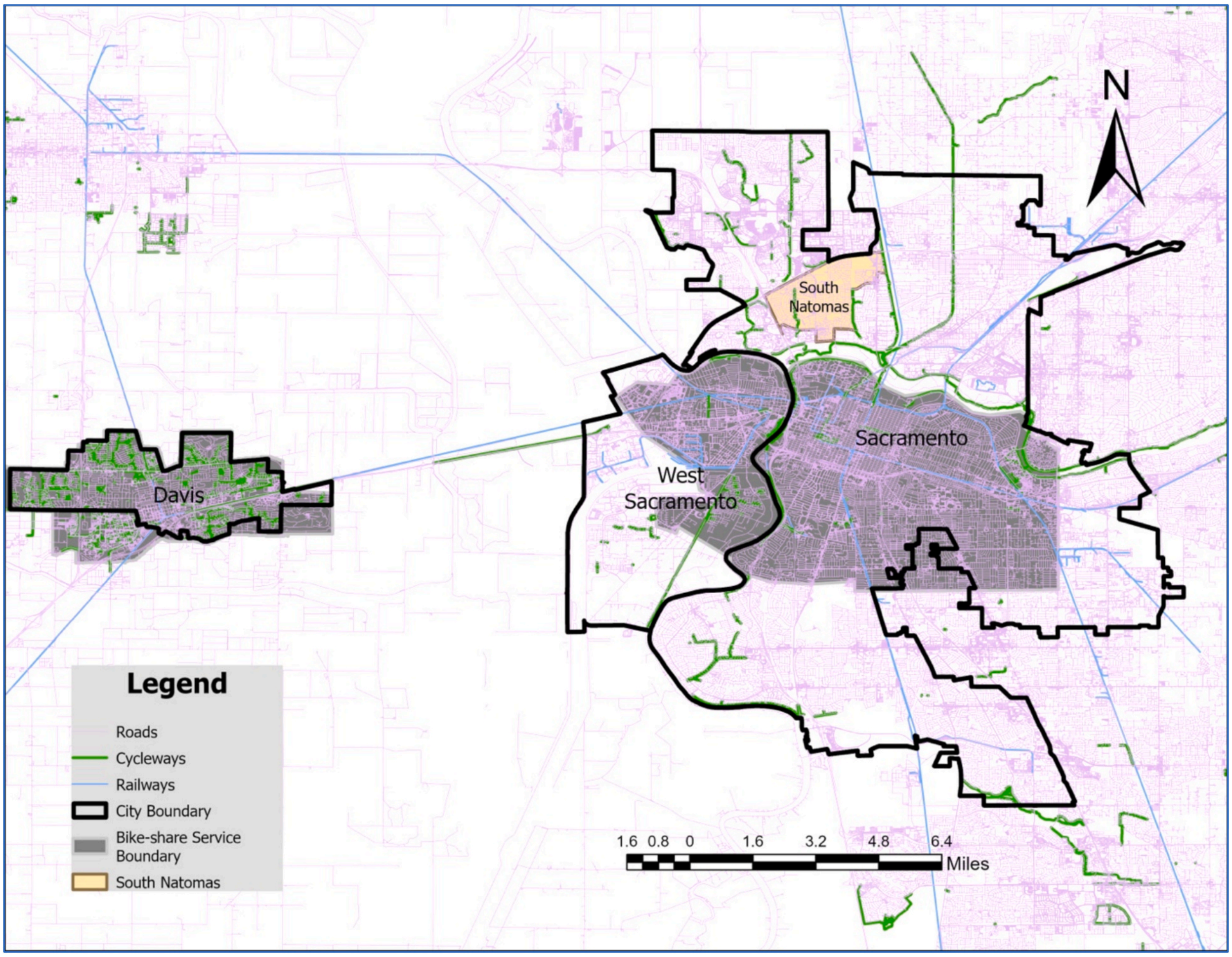

Fig. 1. Study area map.

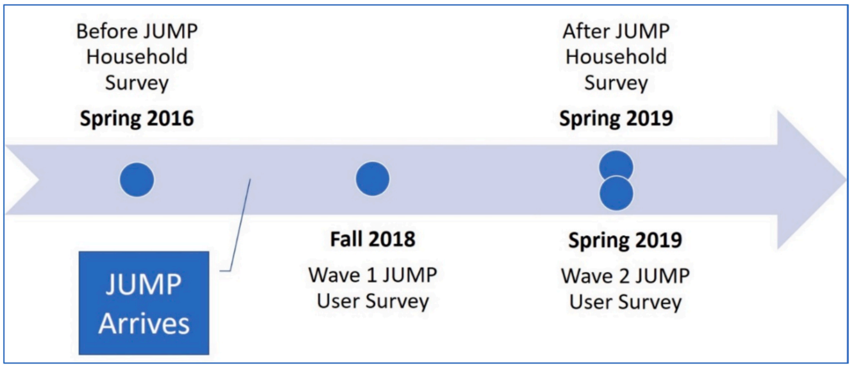

Fig. 2. Timeline of household and bike-share user surveys with respect to bike-share service arrival.

3.3. Modeling approach and dataset options

3.3.1. Dependent variables

As noted in the introduction, the objective of this study is to understand the factors that influence both the adoption and use of the bike-share service. Theory suggests that these two decisions (whether to use the service and, if so, how much) are closely related and can even be viewed as jointly determined, i.e., an appropriate econometric framework is one of discrete/continuous choice. We, therefore, use an integrated modeling framework that determines the two outcomes simultaneously. The decision to adopt is a binary discrete choice (1 = yes, 0 = no), and use is a measure of how *frequently* the service was used over a prescribed unit of time. Data on the adoption and use decisions come from the household and user surveys, respectively.

Early in the household survey, respondents were asked, *"Have you ever used the JUMP bike or scooter share in Sacramento, West Sacramento, or Davis?"* Because the target population of the household sample is the general population in the JUMP service area, this variable was used to understand the bike-share service adoption decisions of individuals. As noted previously, users identified by this question were given the option of being re-routed to the bike-share user survey (although, to reduce the risk of non-response, they were also allowed to remain). Roughly 50 % of respondents elected to re-route themselves to the user survey (with implications to be discussed later); however, 91 respondents, who claimed to be users, stayed on in the household survey.

Measurement of bike-share system use behavior is only feasible for those who have adopted the service and who filled out the user survey. For this study, use frequency is determined based on responses to the following question: "*In the past 28 days, how many JUMP trips did you make?*" In the survey, respondents were asked to use their phone app or online account to retrieve the exact number of trips in the past 28 days. There are multiple options for constructing a dependent variable and estimating models using these responses. Specifically, each respondent provided a numerical count for trips (which ranged from 0 to over 200).[1] This measure could be treated as a continuous response (e.g., in a regression model) or as count data. However, for this study, we subdivided their use frequency into four ordered classes and employed an ordered logit model. The categories were defined as: Minimal user (0 times), Infrequent user (1 to 4 times), Regular user (5 to 10 times), and Frequent user (more than 10 times). Frequency distributions of these classes for the two data sets are reported in Table 2.

3.3.2. Basic framework

Binary choice models are typically formulated assuming an unobservable latent utility index for individual n of the form.

$$u_n = \alpha + x_n^{'}\beta + \epsilon_n \tag{1}$$

where in this case u_n measures the individual's utility for adopting the service, x_n is a vector of observable explanatory variables for individual n, α, and β are parameters, and ϵ_n is a random disturbance term representing factors unobservable by the analyst. In our context, the binary dependent variable $y_n = 1$ if the individual adopts the service and 0 otherwise. The choice to adopt occurs if the utility index exceeds the threshold value of 0.

This could be extended to a parsimonious discrete/continuous model by assuming the utility index is instead a measure of an individual's tendency to use the service. Imposing the strong assumption that the observed use frequency $y_n = u_n$ when $y_n > 0$, a positive use frequency could then be interpreted as a direct indicator that the individual is an "adopter." In this case, if u_n is a continuous variable and ϵ_n is assumed to be normally distributed, this yields a Tobit model—see e.g., Cameron and Trivedi (2005, section 16.3).

However, in our case, these assumptions are clearly too strong, and the Tobit model is almost certainly mis-specified. Specifically, a utility index for the decision process of choosing *whether* to adopt is unlikely to identically coincide with that used for a representation of the use frequency decision. Moreover, in our case, we have data that allows the representation of the two processes to be separated. Specifically, the collection of frequency data is limited to known adopters over a specific 28-day window. The frequency measure is, therefore, highly truncated, and there are many individuals who (despite being known adopters) have an observed frequency of '0.' At the same time, we have a separate sample (the household survey) that directly measures the binary (0/1) adoption decision, i.e., the data collection process does not rely on a frequency count of '0' as an indicator of non-adoption. Finally, we think it is highly unlikely that a linear specification can be used for directly modeling use frequency.

For the above reasons, we adopt a framework relying on utility index(es) of the form in Eq. (1) that allows for a range of specifications and testing for both adoption and use behaviors, including the case where the decision processes are tightly coupled. Specifically, for use frequency we specify u_n^o as an index of an individual's use tendency, but code the use outcome variable y_n^o using the four frequency categories defined above. We adopt the ordered logit model for this data generation process:

$$y_n^o = \begin{cases} 1 \text{ if } u_n^o < \tau_1 \quad (0\, times) \\ 2 \text{ if } \tau_1 \le u_n^o < \tau_2\, (1 - 4\, times) \\ 3 \text{ if } \tau_2 \le u_n^o < \tau_3\, (5 - 10\, times) \\ 4 if u_n^o \ge \tau_3 (>10\, times) \end{cases} \tag{2}$$

where $u_n^o = x_n^{o'}\beta + \epsilon_n^0$, the $\tau_i' s$ are threshold parameters, and the disturbance term ϵ_n^0 is IID Gumbel.

The assumptions $x_n^o = x_n$ and $\epsilon_n^0 = \epsilon_n$ yield a parsimonious formulation that assumes a single index determines both adoption and use, where the adoption decision is binary logit. However, these are strong assumptions, and the two decision processes, while sharing overlapping effects/features, might have elements that differ. For these cases, so-called two-part (hurdle) models have been sugges-

[1] Note that this procedure for collecting use data is subject to truncation effects, that is, for any specific 28-day period, it is possible for someone who is a regular user to nevertheless report zero trips.

Table 2
Descriptive statistics of the variables used in the study.

Variable	HH Survey only	User Survey	HH Survey sample	Pooled Data	Study Area
Sample size	843	374	944	1217	–
Adoption	11 %	100 %	20 %	38 %	–
Davis	15 %	18 %	14 %	16 %	79,252**
Sacramento (Downtown)	66 %	67 %	67 %	66 %	189,972**
West Sacramento	19 %	15 %	19 %	18 %	55,740**
Woman	54 %	43 %	54 %	51 %	52 %
Age (mean)	51	36	49	46	–
Student	8 %	26 %	9 %	13 %	32 %***
Low Income*	15 %	20 %	14 %	16 %	43 %
Middle Income*	60 %	57 %	60 %	59 %	41 %
High Income	25 %	23 %	25 %	25 %	16 %
Race (White)	78 %	68 %	78 %	75 %	62 %
Employed	64 %	86 %	66 %	71 %	–
College Education	75 %	79 %	76 %	77 %	58 %
Mean Bike-share availability score	0.17	0.51	0.20	0.28	–
Bike-share use			(101 response)	(374 response)	
0	–	25 %	43 %	25 %	–
1 to 4	–	30 %	33 %	30 %	–
5 to 10	–	22 %	22 %	22 %	–
More than 10	–	24 %	2 %	24 %	–
Attitude statements**** (mean)*****					
Like bike fun	4.0	4.5	4.0	4.1	
Like bike	3.8	4.5	3.9	3.98	
Enjoyable	4.0	4.5	4.1	4.1	
Pleasant	4.0	4.5	4.1	4.1	
Need car	3.9	3.5	3.9	3.8	
Need car shopping	3.9	3.5	3.8	3.8	
Try limit driving	3.3	3.5	3.3	3.4	
Social pressure healthy	4.1	4.4	4.2	4.2	
Social pressure Fun	3.8	4.1	3.8	3.8	
Social pressure Safe	3.3	3.4	3.3	3.2	
Social pressure Should bike	2.7	3.2	2.8	2.9	

Source: US Census (US Census Bureau 2021), Household Survey and Bike-share User Survey 2019.
Note: *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.
** Calculated based on individuals located within the selected block groups that share bike-share service boundary.
*** A large percentage of the students is due to Davis, a college town that has a 68% student population, West Sacramento has a 16% student population, and downtown Sacramento has a 20% student population
**** For knowing the actual statements, use Fig. 3 as in this table, we report shorter versions of the statements.
***** For each statement in the table, 1 indicated “strongly disagree”; 2, “disagree”, etc., and based on this, we computed the mean.

ted—see e.g., Cameron and Trivedi (2005, section 16.4)—and we consider this possibility here.[2]

The framework described thus far employs the standard approach of using observable explanatory variables (e.g., socio-demographics). Our models include those that might possibly explain adoption and/or use decisions (e.g., gender, income, education level, student status, and geographic location). In addition, we developed an index to represent a potentially important level of service attribute: shared e-bike availability. Finally, consistent with developments in the travel demand literature on modeling mode choice, we extend the framework to include unobservable latent variables associated with underlying attitudes that could affect adoption and use decisions and incorporate responses to attitudinal measurement scales collected in our surveys. The final modeling framework, depicted in Fig. 3, yields Integrated Choice and Latent Variable (ICLV) models—see e.g., Vij and Walker (2016) and references therein. Before providing more detail, we first describe the attitude indicators and bike availability index.

3.3.3. Incorporation of attitude indicators

One of the key features of this analysis is the incorporation of attitudes. Unlike socio-demographics, attitudes are latent factors and are not directly observable. However, an individual’s attitudes towards different modes can be inferred from responses to well-designed attitudinal measurement scales, typically the level of agreement/disagreement with statements (Likert scales) in surveys (Choo and Mokhtarian 2004; Daly et al. 2012). Eleven statements in our survey were designed to measure attitudes toward bicycles, cars, and the social environment around bicycling. The level of agreement and disagreement with these statements was measured using

[2] However, note that our data generation process has more information available than is typically assumed by the usual hurdle models, that is, as discussed, we can distinguish between the case of no adoption versus adoption with zero use over a specified time frame.

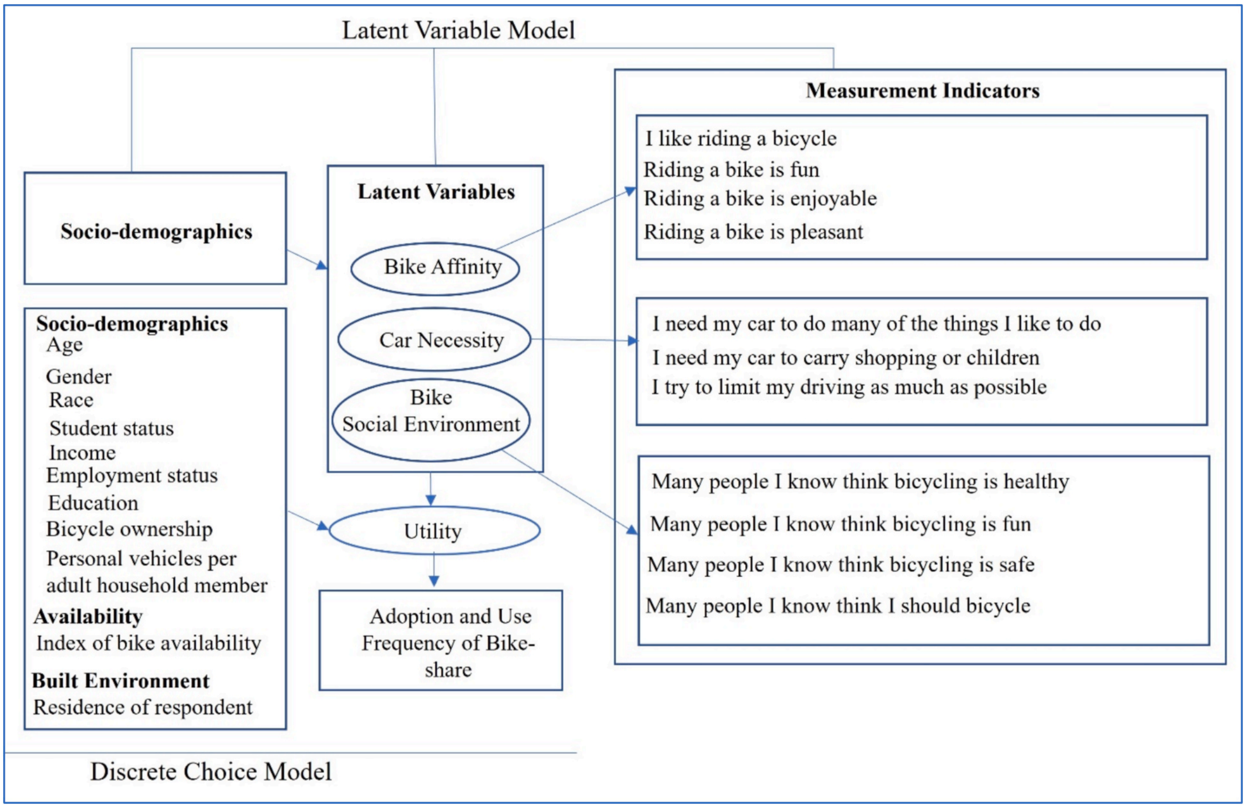

Fig. 3. Theoretical framework of the bike-share adoption and bike-share use model.

a 5-level Likert scale (from “strongly disagree” (1) to “strongly agree” (5)).

The following four statements reflect individual attitudes towards bicycling. The statements were designed based on the studies of Handy, Xing, and Buehler (2010), (Handy and Lee, 2020), and Fitch et al. (2022).

- “I like riding a bicycle”
- “Riding a bike is fun”
- “Riding a bike is enjoyable”
- “Riding a bike is pleasant”

The following three statements reflect individual attitudes towards cars. The statements were designed based on Handy, Xing, and Buehler (2010).

- “I need my car to do many of the things I like to do”
- “I need my car to carry shopping or children”
- “I try to limit my driving as much as possible”

The following four statements reflect individual perceptions of the social environment around bicycling. These statements were designed for this survey based on Ma and Dill (2015).

- “Many people I know think bicycling is healthy”
- “Many people I know think bicycling is fun”
- “Many people I know think bicycling is safe”
- “Many people I know think I should bicycle”

The mean values of the responses to these statements from the survey are provided in Table 2.

The design of these statements suggests a likely pattern of association with three factors (latent variables) that would be implemented in an ICLV model. This was confirmed via an exploratory factor analysis that yielded three factors (using the criterion of an eigenvalue greater than 1) from the eleven statements, with factor loadings suggesting the dimensions “Bike Affinity,” “Car Necessity,” and “Bike Social Environment.” We used the *factanal* package of R to conduct maximum-likelihood factor analysis using the *varimax* rotation method. The ICLV implementation of these is discussed below.

3.3.4. Dockless bike availability index

Bike availability can be an important determinant of individual-level adoption of a bike-share service (Kabra, Belavina, and Girotra 2019). An increased availability of shared e-bikes expands awareness of the service for non-users and could influence their eventual decision to adopt. High shared bike availability also equates to a higher level of service for users and could influence use rates. For a user to make an e-bike trip, they would need to locate one near their current location when considering this mode. With a dockless bike-share system, the locational distribution of available e-bikes would vary over time, and be a function of how many e-bikes there are in the system, the times and locations where other users leave them, and any redistribution activities by the service. To capture this factor, we constructed a bike availability index.

For purposes of this study, we developed an index based on GPS coordinates for addresses of key locations provided by respondents (home and/or work and/or school, if relevant). We used 26 days of bike locations and their durations available from General Bikeshare Feed Specification (GBFS) data for the JUMP service between April 9, 2019 and May 4, 2019, i.e., for the period just prior to survey data collection. Using GIS tools, an area with a 400-meter radius was created around the center of each respondent's location(s), and the total duration of shared bike presence within the area (measured in seconds) was computed for the 26-day period. This area roughly corresponds to locations within a five-minute walking distance. This was chosen because 83 % of survey respondents indicated they would be willing to walk this far to obtain an e-bike for a 15-minute ride (Fukushige, Fitch, and Handy 2021). To produce an index of relative availability/exposure, each respondent's total was standardized (to a 0 to 1 scale) by subtracting the minimum value in the dataset and dividing by the range (max–min).

3.3.5. Model specifications

We considered multiple model specifications for the joint determination of adoption and use based on the framework discussed earlier. We estimated and tested versions that included observable explanatory variables only and observable explanatory variables plus attitudes. Descriptive statistics for these variables for different samples (and combinations of samples) are provided in Table 2. Sampling-related issues will be discussed later.

As a starting point, first consider a utility index function (logit linked) that includes both observable and unobservable explanatory variables (latent attitude variables), consistent with Fig. 3:

$$\begin{aligned} u_n = {} & ASC + \beta_1 BikeAvailability_n + \beta_2 Female_n + \beta_3 Home_{Davisn} + \beta_4 Home_{WestSacramento_n} + \beta_5 Age_n + \beta_6 RaceWhite + \beta_7 Employed_n \\ & + \beta_8 IncomeLow_n + \beta_9 IncomeMiddle_n + \beta_{10} Student_n + \beta_{11} CollegeDegree_n + \beta_{12} BicycleOwnership_n \\ & + \beta_{13} PersonalVehiclePerHouseholdMember_n + \Gamma_1 BikeAffinity_n + \Gamma_2 CarNecessity_n + \Gamma_3 BikeSocialEnvironment_n + \epsilon_n \end{aligned} \tag{3}$$

Here, we extend the earlier general notation to capture the specifics of our application. This function can be used for modeling binary adoption choices using an ICLV model. It includes an alternative specific constant (ASC) (denoted α earlier) and coefficients for observable explanatory variables (β_i's) and for latent variables (Γ_i's). In this specification, all the observable variables (except *Age*) are categorical with two or more levels, implemented using 0/1 dummy coding with the usual implication that one of the levels is the "base level" (with a coefficient of zero). The *Age* variable, plus the three latent variables, are continuous (metric). As discussed previously, a highly parsimonious model that simultaneously explains both the binary choice and the ordered level-of-frequency measure would use the same utility index above without the ASC, plus three threshold parameters (τ_i's).

In the ICLV model, the eleven observed attitudinal measurements discussed earlier provide the information to help identify the values of three latent variables for each respondent. In our models, we assume a factor analytic structure captured by a so-called measurement equation:

$$i_n = Dx_n^* + \eta_n \tag{4}$$

where i_n is a vector of measurement indicators (the eleven attitudinal scales, standardized to have a mean of zero and variance of one), D is an 11x3 matrix of parameters representing the sensitivities of the measurement indicators to the vector of three latent variables x_n^*, and η_n is a vector of stochastic disturbances that are independent and normally distributed with mean 0 and standard deviation (sigma) σ_k, where k denotes the k^{th} attitude statement (Vij and Walker 2016).

The latent variables represent unknown attitudinal constructs; however, it is possible that these attitudes could be a function of observable variables as modeled by the following structural equation:

$$x_n^* = Ax_n + \nu_n \tag{5}$$

Where A is a matrix of parameters and ν_n is a vector of disturbance terms (typically IID standard normal). For our purposes, we hypothesized the following structural equations:

$$BikeAffinity_n = A_{BA,Female} Female_n + A_{BA,RaceWhite} RaceWhite_n + A_{BA,Home_{Davis}} Home_{Davisn} + \nu_{2n} \tag{6.1}$$

$$CarNecessity_n = A_{CN,Female} Female_n + A_{CN,LowIncome} LowIncome_n + A_{BA,Home_{Davis}} Home_{Davisn} + \nu_{1n} \tag{6.2}$$

$$BikeSocialEnvironment_n = A_{BSE,Home_{Davis}} Home_{Davisn} + \nu_{3n} \tag{6.3}$$

Having established this framework, it is now possible to give a detailed description of the various model specifications we tested. The description thus far has been for a highly constrained, parsimonious model where all the parameters defined above are estimated. However, it is possible to relax the assumption that the utility indexes for both the binary choice and the use frequency are identical. In the extreme, unconstrained case, a completely independent set of β_i's and Γ_i's can be estimated for the binary choice and ordered logit models, respectively. Note that all the other parameters would be estimated as prescribed.

In our study, these two versions (completely constrained and unconstrained) represent two extreme options. It is also possible to estimate models that are intermediate between the two extremes, where some of the same coefficients are used in both models. Note that in this approach, statistical tests of model equality are straightforward using likelihood ratio tests. Finally, we noted previously that we estimated versions with and without latent variables. In what follows, we report results for intermediate models we judged to generally be the "best," but where we use the same specifications with and without latent variables. Maximum simulated likelihood estimates for all models were computed in R Studio using the Apollo choice modeling package (Hess and Palma 2019) with the BGW estimation algorithm (Bunch, Gay, and Welsch 1993). These ICLV models require maximum simulated likelihood because the distributional assumptions of Eqs. (4) and (6) yield log-likelihood expressions that require evaluation of integrals—see, e.g., Vij and Walker (2016). We implemented the approach using 2000 Sobol draws as documented in the Apollo manual (Hess and Palma 2019, 2023).

3.3.6. Sampling issues

One final technical issue on estimation remains. Maximum likelihood estimates for models specified in this manner are only consistent if the data set used for estimation is obtained using exogenous random sampling (see, e.g., Cameron and Trivedi, Chapter 16) (Cameron and Trivedi 2005). Technically, the only subset of data that might meet this criterion would be from those respondents who were recruited for the household survey using address-based sampling. The initial household sample size was 988, of which 44 were unusable, leaving a total potential sample size of 944. Of these, 843 completed the household survey (752 non-adopters and 91 adopters), and approximately 101 adopters chose to be diverted to the user survey and completed it. In addition to these 101 respondents, 273 current Jump users were recruited for the user survey from flyers attached to e-bikes and other intercept methods, as described earlier (for a total of 374). One potential issue with this sampling procedure is that the probability of being recruited increases as a function of use frequency.

Given these data and the range of possible modeling assumptions, there are multiple options for model estimation, each with pros and cons. Descriptive statistics for four different data configurations are provided in Table 2: Household Survey only (843 respondents), User Survey only (374 respondents), Household Survey sample (HH only plus diverted users), and Pooled Data (843 + 374 = 1217).

Jointly estimating adoption and use models using pooled data maximizes sample size, but respondents are from two different sampling approaches. With respect to the decision of whether to adopt, a portion of the pooled sample is a "choice-based sample." Although it might be possible to develop an approach that takes this into account, how to do this is not immediately obvious or straightforward. With respect to the frequency of use data, part of the sample could be biased upward, as noted previously. The alternative is to limit model estimation to only those data originally sampled for the household survey. The estimates are more likely to be consistent, but the sample size of respondents providing use frequency data is notably smaller. In either case, frequency of use data from adopters who only completed the household survey are not available (and treated as missing in the estimation).

Finally, although the household sample has arguably better sampling properties because it is address-based, such a sample is truly "random" only in theory, and self-selection bias is always a concern: people who choose to respond may have behavioral and attitudinal predispositions toward bike-share than respondents from a truly random sample.

3.3.7. Other data limitations

The models used in this study require complete data for a relatively large number of variables. For both the household survey and bike-share user survey, missing data resulted in a sizeable loss of usable observations. This problem was particularly acute in the bike-share user survey. The bike-share user survey is likely more burdensome than the household survey as the average duration of survey completion is higher for the bike-share user survey than for the household survey.

Another potential data-related concern is that the data come from a very specific geographical location that could limit the extent to which findings and conclusions can be generalized. However, there is a certain amount of diversity across the three sub-markets comprising the study area, and a key feature of our modeling methodology is to aggressively identify detailed effects as a function of both socio-demographics and attitudes, which can mitigate these concerns to a degree.

Finally, another data-related limitation relates to the role of pricing effects. First, our data are for a single vendors' offering in a single market, so there is no systematic variation in price that might be present in, e.g., a study that samples and compares across many cities. Second, the timing and focus of the study are on an introduction of an offering in a very new product category by one of multiple start-up companies. At the time, introductory prices were relatively low with a variety of promotions in a fluid environment, in contrast to what has been occurring as the market matures post-pandemic. Our focus here is on adoption and utilization decisions in response to an introduction.

3.4. Modeling implementation

We focus on the main research question, *"How do different socio-demographic characteristics, latent attitudes towards modes and the* *social environment, and availability of the service influence the adoption and use of electric dockless bike-share?"* To address this question, we investigated several models by applying the framework from the model formulation section. Within the framework, there are many possible specifications lying between two "extreme endpoints": a fully constrained model where the latent index function parameters in Eq. (1) are identical for both the adoption and frequency choice processes, and a fully unconstrained model where the adoption and frequency models are essentially independent. Intermediate between the two extremes are specifications where parameters for some explanatory variables are the same for both adoption and frequency choices, but others differ. Theory suggests that the two choice processes could be strongly linked.

In the econometrics literature on two-part hurdle models, a frequent hypothesis for modeling linkages between two processes is that their unobservable disturbance terms (usually normally distributed) are correlated. Our approach implicitly incorporates this concept by introducing additional latent variables that are hypothesized to arise from unobservable attitudes. In the absence of additional information, implementing a random-effects mixture model (analogous to mixed logit) might be a possibility. However, because both surveys collected a common set of attitude-related measurements, we can implement ICLV-type models as previously discussed. Our approach was to estimate and test model alternatives in pairs: one version without latent variables and a corresponding one with latent variables. This allows a systematic comparison to assess the impact of introducing latent variables.

Finally, for any pair of models, we estimated the same specifications for the two different datasets (pooled and household only) discussed previously. Results can be compared to assess any implications related to sampling issues.

As a starting point, we first estimated the two "endpoint" models (completely constrained and completely unconstrained) and then tested the intermediate specifications. Within this framework, nested intermediate models can be directly compared using likelihood ratio tests. As might be expected, the hypothesis that the constrained and unconstrained models are equivalent was strongly rejected. After testing a variety of alternatives, we adopted a final (intermediate) specification for which latent index coefficients for living in Davis, gender, race, and being a student can be viewed as the same for the two decision processes. These models are not statistically different from the unconstrained model.

4. Results and discussions

Results for the four final models are provided in Table 3.

Before focusing on behavioral implications, we first consider systematic differences across the two types of data sets (Pooled versus Household Survey). For the (binary) adoption decision, the latent index function includes a dedicated intercept term (or, in the context of discrete choice, an alternative-specific constant, or ASC). For the Household Survey data models, the ASC was small and statistically insignificant. In contrast, the ASC was notably larger, with higher significance for the pooled data. This effect was expected because the pooled data consisted of the household survey data plus additional observations from individuals who are known adopters. If the ASC is sufficient for capturing the average of unobserved effects in the combined sample, the hope is that the conditional effects of explanatory variables on adoption are the same across the two samples, so that the larger sample size of the pooled data will improve the precision of coefficient estimates. This is consistent with the observed results: the estimated coefficients for explanatory variables unique to the adoption decision are in fact, quite similar across the four models, but with larger t-statistics observed for the pooled data models.

The two data sets are also expected to be systematically different in their use frequencies. As discussed previously, for the sampling approach used to recruit individuals directly into the user survey, the probability of sampling an individual is expected to increase with their use frequency. The use frequencies for the pooled sample are expected to be systematically higher than those from the Household Survey, which is confirmed in Table 2. However, when it comes to modeling, Table 2 indicates that all four models are limited in their ability to distinguish among the first three categories [Minimal, Infrequent, and Regular] versus the fourth [Frequent (more than 10 times in 28 days)]. That is, for all four models, the first two thresholds (τ_1 and τ_2) are statistically insignificant, whereas τ_3 is statistically significant. To directly address the sampling issue, the pooled data models include a dummy variable (Household survey dummy, in Table 3) that identifies respondents re-routed from the Household Survey to the User Survey. Its coefficient is negative and highly significant; that is, the latent index for use frequency is systematically shifted downward relative to the set of thresholds. Moreover, the thresholds for the Household Survey models are systematically higher than for the pooled models (although, again, only τ_3 is statistically significant). Having addressed these main systematic differences, we turn to a more detailed discussion of the effects of socio-demographics.

4.1. Effects of socio-demographics common to adoption and use

Four factors are specified to have a common effect on the utility index for both adoption and use frequency: Davis residency, woman, student, and race (white). Comparing the effects of each factor across the four models, they are usually similar in terms of sign and magnitude, and the coefficients for the pooled data models are more statistically significant than those for the Household Survey models (for reasons discussed previously).

The large negative effect of Davis residency on both adoption and use frequency (relative to the base level of Downtown Sacramento residency) is striking and implies an overall negative "utility" for bike-share. Davis is well known for its strong bicycling culture: the city has a substantial greenbelt system with off-street shared-use paths as well as an extensive network of on-street bike lanes, with very high ownership and use of traditional non-electric bicycles. Although residents might be expected to be highly receptive to the benefits of dockless electric bike-share, this result is consistent with the notion that they are already meeting their needs with existing bikes (which could also include personally owned e-bikes), and so they have a systematically lower adoption and use frequency for the

Table 3
Model results for bike-share adoption and use frequency using pooled data and household survey data.

	Pooled data models (with and without latent variables)				Household survey data models (with and without latent variables)			
Parameters of the joint model	*Estimate*	*t-ratio**	*Estimate*	*t-ratio**	*Estimate*	*t-ratio**	*Estimate*	*t-ratio**
Parameters common in both adoption and use frequency model								
Davis	−0.7884	−3.11*	−0.5653	−2.36*	−1.0721	−2.53*	−0.6871	−1.61
Woman	−0.1797	−1.14	−0.2705	−1.82*	−0.1288	−0.62	−0.1615	−0.83
Student	0.4736	1.81*	0.3664	1.52	−0.0846	−0.23	0.0816	0.24
Race (White)	0.1922	1.12	0.2984	1.85*	0.4426	1.84*	0.4518	2.08*
Parameters unique to the adoption model								
ASC	−0.2032	−0.29	0.2030	0.30	−0.4896	−0.56	−0.3136	−0.38
West Sacramento	0.4092	1.50	0.3161	1.27	0.5851	2.17*	0.5583	2.28*
Availability Index	2.7602	6.08*	2.9909	6.87*	2.9542	5.35*	2.9419	5.70*
Age	−0.0492	−6.13*	−0.0483	−6.56*	−0.0485	−5.18*	−0.0443	−5.20*
Low income (base= High income)	−1.0510	−2.59*	−0.9090	−2.50*	−1.1229	−2.32*	−1.0065	−2.25*
Middle income (base= High income)	−0.7350	−2.81*	−0.6582	−2.70*	−0.5221	−1.87*	−0.4592	−1.79*
Employed	0.1708	0.65	0.1030	0.40	−0.0805	−0.26	0.0458	0.15
College Education	0.3421	1.21	0.2185	0.83	0.1722	0.53	0.1918	0.61
Personal vehicles per adult	−0.1732	−0.67	−0.3099	−1.37	0.0450	0.17	−0.0987	−0.41
Missing dummy for vehicle per adult**	1.3062	3.00*	1.1840	3.05*	−0.2797	−0.49	−0.1446	−0.25
Bicycle ownership	−2.2508	−7.75*	−2.1718	−7.68*	−1.4531	−4.90*	−1.3515	−4.74*
Missing dummy for bicycle ownership**	2.1624	8.32*	1.6849	7.47*	1.2550	4.57*	0.7995	3.32*
Bike affinity (latent variable)	0.8405	6.16*			0.8231	5.24*		
Car necessity (latent variable)	−0.2032	−1.68*			−0.0657	−0.50		
Bike social environment (latent variable)	0.2226	1.62			0.3164	2.07*		
Parameters unique to the bike-share use frequency model								
tau use bikeshare1*** (τ_1)	−1.2733	−1.41	−1.6330	−1.84*	1.0270	0.45	1.0890	0.45
tau use bikeshare2*** (τ_2)	0.4231	0.47	−0.0251	−0.03	2.8148	1.20	2.6667	1.08
tau use bikeshare3*** (τ_3)	1.5972	1.72*	1.0674	1.19	5.3614	2.14*	5.0845	1.98*
Household survey dummy	−1.7693	−5.60*	−1.6746	−5.54*	–	–	–	–
West Sacramento	−0.5907	−1.47	−0.5981	−1.54	−0.2868	−0.42	−0.5827	−1.03
Availability Index	0.0960	0.16	−0.0338	−0.06	0.7904	0.49	0.6813	0.46
Age	0.0191	1.20	0.0193	1.27	0.0073	0.21	0.0161	0.46
Employed	0.8773	1.93*	0.7913	1.74*	0.8032	0.74	1.0414	0.86
Low income (base= High income)	0.3363	0.72	0.4134	0.88	−0.5436	−0.46	−0.1268	−0.11
Middle income (base= High income)	0.0274	0.08	−0.0135	−0.04	−0.3124	−0.52	−0.1918	−0.37
College Education	−0.4752	−1.19	−0.4864	−1.27	−0.3975	−0.45	−0.4198	−0.52
Personal vehicles per adult	−0.4136	−1.08	−0.7537	−1.96*	0.2102	0.43	−0.0447	−0.10
Missing dummy for vehicle per adult**	−1.2251	−2.61*	−1.3632	−3.02*	−0.4587	−0.17	0.3277	0.15
Bike affinity (latent variable)	0.0217	0.12			0.0336	0.08		
Car necessity (latent variable)	−0.5387	−3.46*			−0.7174	−2.07*		
Bike social environment (latent variable)	0.1284	0.79			0.5382	1.19		
*Measurement models of eleven statements**** based on Eq. (4) and Fig. 2*								
Like bike fun	0.8291	21.55*			0.8267	28.64*		
Like bike	0.8250	19.59*			0.8403	25.23*		
Like bike enjoyable	0.8146	21.49*			0.8081	28.95*		
Like bike pleasant	0.7288	19.49*			0.7140	23.16*		
Need car	0.8082	13.98*			0.7495	13.09*		
Need car shopping	0.6867	14.03*			0.6441	11.51*		
Try limit driving	−0.4634	−10.13*			−0.4273	−8.89*		
Social pressure healthy	0.4167	13.01*			0.4073	11.93*		
Social pressure fun	0.6015	15.26*			0.5546	10.99*		
Social pressure Safe	0.3473	7.76*			0.3532	6.85*		
Social pressure should bike	0.4628	9.89*			0.3768	7.30*		
Sigma like bike fun******	0.3423	20.25*			0.3571	18.73*		
Sigma like bike******	0.5034	14.01*			0.4864	12.97*		
Sigma like bike enjoyable******	0.3394	13.71*			0.3455	12.14*		
Sigma like bike pleasant******	0.3765	13.47*			0.3915	12.05*		
Sigma need car******	0.7089	12.67*			0.6834	12.71*		
Sigma need car shopping******	0.9210	25.24*			0.8896	21.22*		
Sigma try limit driving******	1.0375	38.74*			1.0311	37.55*		
Sigma Social pressure healthy******	0.6057	20.90*			0.5891	17.81*		
Sigma social pressure fun******	0.5625	15.28*			0.5858	13.29*		
Sigma social pressure safe******	0.8719	37.05*			0.8423	31.00*		
Sigma social pressure should bike******	0.9032	35.24*			0.9024	34.50*		

(continued on next page)

Table 3 (*continued*)

	Pooled data models (with and without latent variables)			Household survey data models (with and without latent variables)		
Structural equation models for bike affinity and car necessity latent attitudes based on Equation (5.1) and Equation (5.2)						
Woman (bike affinity attitude)	−0.1167	−1.48		−0.0659	−1.02	
Race white (bike affinity attitude)	−0.0218	−0.30		−0.0228	−0.40	
Davis (bike affinity attitude)	0.0991	1.06		0.0687	0.81	
Woman (car necessity attitude)	0.1832	2.98*		0.1415	2.08*	
Low Income (car necessity attitude)	−0.4009	−3.11*		−0.4571	−2.72*	
Davis (car necessity attitude)	−0.3734	−3.02*		−0.4319	−2.81*	
Davis (Bike social environment)	0.2242	2.07*		0.3044	2.36*	
Number of Parameters	64		29	63		28
Number of Observations*****	Adoption: 918 Use Frequency: 259		Adoption: 918 Use Frequency: 259	Adoption: 737 Use Frequency: 78		Adoption: 737 Use Frequency: 78
Log Likelihood	−12183.75		−691.09	−9529.7		−387.44
BIC	24804.11		1543.33	19475.37		896.86
AIC	24495.49		1440.18	19185.41		830.87

Note:

* We labeled the significance of a variable based on a 10% significance level where the t-statistics are greater than or equal to 1.65 (absolute value).

** We had some missing values where some individuals did not report the number of adult household members and whether they own a personal bicycle. Including these variables in the model reduces the number of observations due to missing values. To avoid that, we used a "0″ value for the variables for a missing observation and then added a missing dummy variable to capture that. For personal bike ownership, we added a "0" for the missing value and also added a missing dummy variable to capture that.

*** These are developed based on Eq. (2).

**** For knowing the actual statements for these, use Fig. 3 as in this table, we report shorter versions of the statements.

***** These observations are different from Table 2 due to missing data.

****** Standard deviation (sigma) σ_k, where k denotes the kth attitude statement.

bike-share service. An interesting observation is that, for both the Household Survey and Pooled data models, the magnitude and significance of this factor both increase when attitudes are included in the specification. Davis residents do have systematically different attitudes related to this shift, as discussed later. That is, Davis residency has both a direct and an indirect effect on adoption and use frequency.

Apart from the location of residence, we tested the effect of built-environment variables from the Smart Location Database provided by the Environmental Protection Agency (EPA), but none of them were statistically significant in our modeling. We, therefore, dropped those variables for reasons of parsimony.

The coefficients for woman are negative and similar in magnitude across all four models, nominally indicating that its effect is to lower the likelihood of both adoption and use frequency. However, the woman coefficient is only statistically significant for the pooled data model with no attitudes (perhaps due to the larger sample size). It is therefore notable that the coefficient for woman decreases in magnitude and becomes statistically insignificant when attitudes are included. As discussed later, the woman coefficient in the structural equation for the car necessity attitude is statistically significant, and so the effect of being a woman on adoption and use is solely indirect. (This is in contrast to Davis residency, which has both direct and indirect effects.) Separating these types of effects is a notable feature of using ICLV modeling.

In contrast to being a woman, the effect of being a student on adoption and use frequency is positive in the pooled data models (although, like the woman effect, it is not statistically significant in the household data models). Also, in contrast to the woman effect, the (direct) student effect is larger in magnitude and statistical significance when attitudes are added. For race (white), the coefficients are positive, and are statistically significant in three of the four models. The effect size of race (white) decreases and becomes less significant when attitudes are included.

4.2. Adoption-specific and use-specific socio-demographic effects

Separate effects for adoption and use frequency were estimated for the following factors: West Sacramento residency (base level = Sacramento residency), age (continuous effect), income (three categories), employment, and college education. The primary finding is that the effects of most of these factors were generally significant for the adoption decision but not the use decision. Moreover, the effect sizes and significance levels were similar across all four models.

The two demographic factors with the most significant effects on adoption are income and age. Respondents with high income (base level; see Table 2 for definitions) are significantly more likely to adopt the service (that is, the coefficients of middle and low income are negative and significant), and the size of the negative coefficient on low income is notable. This finding is consistent with previous bike-share studies, which find that low-income individuals are much less likely to adopt (Grasso, Barnes, and Chavis 2020; McNeil, Broach, and Dill 2018; Shaheen et al. 2014; Stromberg 2015). In contrast to adoption, the effects of income level on use frequency are lacking in statistical significance. However, when including attitudes, there is an indirect effect of low income on usage rate that must be considered (discussed below).

The adoption coefficients for age are negative, highly significant, and similar across all four models, indicating that the likelihood of adoption decreases with age. This is consistent with the existing bike-share literature that shows that younger individuals are more likely to adopt the service (Fuller et al. 2011; Hoe 2015; Shaheen et al. 2014). In contrast, the age effect on use is positive, although not significant. The effect of employment on adoption is not statistically significant, but the effect on use is positive and significant (for the Pooled data models). The effect of a college education on adoption is positive and similar across all models but not statistically significant. In contrast, the effect is negative for use, but also not significant.

The effect of West Sacramento residency is mixed. Coefficients on the adoption decision for the Household Survey data models are positive and significant, providing a contrast to the other two cities (Davis and Downtown Sacramento). In contrast, the signs are negative and marginally significant for the use decision in the Pooled data models.

4.3. Effect of bicycle and vehicle access

Early the model development process we identified the Davis residency effect discussed earlier, which raised the question of whether bicycle ownership might be related to adoption and use decisions. A similar question arises regarding vehicle availability, for which a typical measure is number of vehicles per adult in the household. We elected to include these variables in our analysis; however, we encountered a substantial amount of missing data for these measures. Rather than drop observations, we included separate coefficients for dummy variable indicators of missing data.

Our results indicate that access to personal bicycles does indeed have a significant, negative affect on the adoption decision. This is consistent with expectations, as individuals with a personal bicycle may see less need to use a shared bicycle. Moreover, the estimated coefficients are significant with a similar effect size across all four model, that is, the omission of latent attitudes has little effect, indicating that this variable that is a key predictor of adoption decisions. However, this variable had no effect on the frequency of use decision, and so is omitted from the models.

In contrast, our models show that the number of available personal vehicles per adult household member does not significantly influence the decision to adopt shared electric bikes: even though the coefficients have the expected negative sign in three of the four models, they are not statistically significant. At the same time, this factor does negatively affect bike-share use frequency in the Pooled data model without attitudes. However, adding attitudes causes the coefficient to get smaller, and become statistically insignificant. It is likely that latent attitudes for car necessity may have captured this aspect. However, we could not find a direct relationship between this factor and any attitudes that were statistically significant.

4.4. Effect of availability index

One unique feature of our work is the creation and use of an availability index for these models. Recall that this index is intended to capture an important feature of floating bike-share systems that could affect both the adoption and use decisions. The large positive bike availability index coefficient for the adoption decision (with both Household Survey data and Pooled data) indicates that controlling for socio-demographics and latent attitudes, the availability of shared bikes is a major determinant of adoption. As discussed earlier, this may be due to an exposure effect that creates increased awareness of the service. A slightly different view is that an increase in perceived availability could increase the perceived utility of the service.

However, the effect of the availability index on the use decision is not significant in any of the models. Overall, the results indicate that the availability index has a much larger influence on adoption than on the usage rate, for reasons discussed earlier. However, this result should be interpreted with caution as our measure of availability is restricted to the home and/or work or school locations of the individual (i.e., places where the individual is likely to visit frequently). In reality, individuals may be exposed to bike-share systems in many locations where individuals perform different types of activities, which may influence their use frequency.

4.5. Results from the measurement models

Before discussing attitude-related effects, we first review results from the measurement models, which establish the numerical coefficients for relationships between the latent variables and the observed attitude indicators from the survey data (as depicted in Fig. 3). The four statements related to personal perceptions of bicycles are positively associated with the bike affinity latent variable, as expected. The four statements related to perceptions of other people's bicycle opinions are positively associated with the bike social environment latent variable. In the measurement models, "I try to limit driving as much as possible" is negatively associated with the car necessity latent variable, while other car-related statements are positively associated, as expected. These results confirm the validity of using these indicator variables as measures for the latent attitude variables.

4.6. Effect of latent attitude variables

Coefficients for all latent attitude variables (i.e., bike affinity, car necessity, and bike social environment) are significant (though bike social environment is marginally significant with t-ratio very close to 1.65) for the adoption decision using the pooled data. Bike affinity and bike social environment are also significant in the household data model. The coefficients are positive and similar for the two data sets. These coefficients indicate that, as attitudes about bikes and the social environment become more positive, the likelihood of adoption increases. On the other hand, the coefficients for these two latent variables are not statistically significant for the use decision.

The results are different for the car necessity latent variable. As the perception of car necessity increases, the likelihood of adoption decreases. However, the influence of this latent variable on adoption is smaller and less significant than the two bike-related latent variables. In contrast, the negative effect of the car necessity latent variable on the use decision is both large and significant. Respondents' perceptions that a car is necessary for the types of trips they make translate directly into less use of bike-share.

4.7. Interaction of socio-demographics with the latent attitude variables

An individual's socio-demographic characteristics and surrounding bike social environment factors play a significant role in shaping their latent attitudes, which in turn affect their adoption and use of the service. The ICLV modeling framework is especially helpful in revealing these relationships through structural equations. A socio-demographic variable that has a significant effect on an attitude that, in turn, has a significant effect on adoption and/or use constitutes an indirect effect. It is possible for a socio-demographic variable to have both a direct effect and an indirect effect on these decisions, as discussed previously for Davis residency.

The structural equation model reveals that individuals with low income tend to have a lower value for car necessity compared to others, perhaps because their economic activities are more limited, which in turn lowers their need for a car. Moreover, because the coefficient on car necessity is negative and significant, this implies an indirect effect whereby low-income individuals have an increased use rate. (This indirect effect is the reason for the decreased significance of the direct effect of low income when attitudes are added to the model.) This indicates, although not directly, that there is an indirect statistically positive effect of being low-income on the dockless electric bike-share use frequency.

In contrast, women have an increased perceived need for a car, which could be due to, e.g., making more trips related to transporting children and shopping. In fact, one of the attitude indicators specifically focuses on shopping and children, and moreover, the need to transport children is an often-cited obstacle to bicycle use by women (Garrard, Handy, and Dill 2012). Recall that car necessity, in turn, has a negative effect on both adoption and use of the service.

Davis residents have significant coefficients with large magnitudes for both car necessity (negative) and bike social environment (positive), as would be expected from our earlier discussion. And, as already noted, even when these effects are taken into account, Davis residency has a negative and significant direct effect on adoption and use due to the highly bike-friendly built environment of Davis and the associated high use of personal bicycles. Finally, with regard to bike affinity, none of the factors included in the structural equation (woman, race(white), Davis residency) are statistically significant.

5. Conclusion

We explored the influence of a variety of factors on the adoption and use frequency of a dockless e-bike-share service introduced in three cities in the Sacramento region. Apart from socio-demographic effects, we explored the influence of the city of residence, mode-related latent attitudes, and bike availability factors using the ICLV modeling framework.

Recall that the context for our study was the opportunity to partner with a vendor to perform a detailed analysis of adoption and usage decisions in a single market in response to the introduction of a new mobility offering in the early stages of the development of this space. As noted in the data limitations section, the research design precludes analysis of pricing effects. Another concern is a potential lack of generalizability due to focus on a single market. However, this is why a key feature of our approach is to develop models that include highly detailed socio-economic, attitudinal, and context effects. As such our results provide a variety of insights of potential value to policy makers (in contrast to, e.g., company decision-makers).

Our results show that low-income individuals are less likely to adopt the bike-share service. However, if they do, our models show evidence of higher use rates due to a lower perception by low income individuals that cars are necessary for their trips. The results of this study suggest that barriers to initial adoption by low-income groups are an important concern. Bike-share operators and cities can collaborate to develop a variety of programs that target lower-income market segments. These programs can assist cities in achieving equity and sustainability goals as bike-share can reduce the use of cars for several trip purposes (Mohiuddin, Fitch-Polse, and Handy 2023). Proper marketing of these programs to low-income groups is also important, as suggested by Dill and McNeil (2021).

Our models show that bike availability in the area around an individual's home, and/or work, and/or school locations positively influences adoption but not use frequency. This effect of exposure on adoption has potentially important implications when considering bike redistribution strategies and policies. Given that the bikes are dockless, this also has significant implications for equity as, with the absence of an appropriate equity-based rebalancing strategy, the bike-share distribution could be highly skewed to certain groups.

Our analysis shows that bike affinity and bike social environment attitudes significantly and positively influence bike-share adoption. However, car necessity attitudes significantly and negatively influence the frequency of bike-share use. This finding has policy implications, as developing positive attitudes toward bikes and fostering a social environment of bicycling at the population level may nudge more individuals to adopt bike-share services. Developing programs to influence the attitudes of individuals at the population level in combination with investing in bike infrastructure can prove to be an effective strategy for increasing the adoption of bike-share. In a prior study that examined data both before and after the bike-share introduction (see Fig. 2), Fitch-Polse et al. (2024) found evidence that the introduction of the bike-share systems positively influenced the bike-related attitudes of both users and non-users of the system (Fitch-Polse et al., 2024).

Another important aspect of including attitudes in the models is that their presence can affect the size and significance of coefficients on socio-demographic and other observable factors. Moreover, the models can clarify whether these factors have a direct or indirect effect (or both) on adoption and use decisions. Models excluding attitudes could lead to spurious conclusions about the role and impact of various factors, potentially affecting policy decisions. As suggested by our model results, the consistent availability of and exposure to the bike-share service can produce a positive loop that may result in higher societal-level adoption of the service as well as encouraging a positive individual attitude towards bicycling. Investing in bike infrastructure can reinforce this effect as it can directly influence the social environment of bicycling. These findings have implications for areas such as Sacramento and other U.S. cities where the official interest in bicycling and investing in bicycle infrastructure is relatively recent.

These findings have implications for both cities and bike-share providers. As dockless systems continue to expand across the country, cities can conduct detailed analyses using the readily available bike-share trip and availability data from General Bikeshare Feed Specification (GBFS) and Mobility Data Specification. Findings from these studies can help cities better address bike-share and mobility access and equity and assist companies in effectively determining their rebalancing strategies to maximize profit while considering equity.

CRediT authorship contribution statement

Hossain Mohiuddin: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **David S. Bunch:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization. **Tatsuya Fukushige:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Dillon T. Fitch-Polse:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Data curation, Conceptualization. **Susan L. Handy:** Writing – original draft, Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization.

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References

Ajzen, I., 1991. The Theory of Planned Behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Ashok, K., Dillon, W.R., Yuan, S., 2002. Extending discrete choice models to incorporate attitudinal and other latent variables. J. Mark. Res. 39 (1), 31–46. https://doi.org/10.1509/jmkr.39.1.31.18937.

Blazanin, G., Mondal, A., Asmussen, K.E., Bhat, C.R., 2022. E-Scooter sharing and bikesharing systems: an individual-level analysis of factors affecting first-use and use frequency. Transp. Res. Part C Emerging Technol. 135, 103515. https://doi.org/10.1016/J.TRC.2021.103515.

Blechar, J., Constantiou, I., Damsgaard, J., 2005. "The Role of Marketing in the Adoption of New Mobile Services: Is It Worth the Investment?" *4th Annual International Conference on Mobile Business, ICMB 2005* 370–76. doi: 10.1109/ICMB.2005.104.

Breengaard, M.H., Henriksson, M., Wallsten, A., 2021. Smart and Inclusive Bicycling? Non-Users' Experience of Bike-Sharing Schemes in Scandinavia." *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in*. Bioinformatics) 12791 (pp), 529–548. https://doi.org/10.1007/978-3-030-78358-7_37.

Buck, D., Buehler, R., Happ, P., Rawls, B., Chung, P., Borecki, N., 2013. Are bikeshare users different from regular cyclists? Transp. Res. Rec.: J. Transp. Res. Board 2387 (1), 112–119. https://doi.org/10.3141/2387-13.

Buehler, T., Handy, S., 2008. Fifty years of bicycle policy in Davis, California. Transp. Res. Rec. 2074 (2074), 52–57. https://doi.org/10.3141/2074-07.

Bunch, D.S., Gay, D.M., Welsch, R.E., 1993. Algorithm 717: subroutines for maximum likelihood and quasi-likelihood estimation of parameters in nonlinear regression models. ACM Trans. Math. Software (TOMS) 19 (1), 109–130. https://doi.org/10.1145/151271.151279/SUPPL_FILE/717.GZ.

Cameron, A.C., Trivedi, P.K., 2005. *Microeconometrics*. Cambridge University Press.

Campbell, A.A., Cherry, C.R., Ryerson, M.S., Yang, X., 2016. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. Transp. Res. Part C Emerging Technol. 67, 399–414. https://doi.org/10.1016/j.trc.2016.03.004.

Chen, Z., van Lierop, D., Ettema, D., 2020a. Dockless bike-sharing systems: what are the implications? Transp. Rev. 40 (3), 333–353. https://doi.org/10.1080/01441647.2019.1710306.

Chen, Z., van Lierop, D., Ettema, D., 2020b. Exploring dockless bikeshare usage: a case study of Beijing, China. Sustain. (Switzerland). https://doi.org/10.3390/su12031238.

Choo, S., Mokhtarian, P.L., 2004. What type of vehicle do people drive? the role of attitude and lifestyle in influencing vehicle type choice. Transp. Res. A Policy Pract. 38 (3), 201–222. https://doi.org/10.1016/j.tra.2003.10.005.

Clewlow, R.R., Mishra, G.S., 2017. Disruptive transportation: the adoption, utilization, and impacts of ride-hailing in the United States. Genome 44 (3), 401–412.

Daly, A., Hess, S., Patruni, B., Potoglou, D., Rohr, C., 2012. Using ordered attitudinal indicators in a latent variable choice model: a study of the impact of security on rail travel behaviour. Transportation 39 (2), 267–297. https://doi.org/10.1007/s11116-011-9351-z.

del Alonso-Almeida, M., 2019. Carsharing: another Gender issue? Drivers of carsharing usage among women and relationship to perceived value. Travel Behav. Soc. 17, 36–45. https://doi.org/10.1016/j.tbs.2019.06.003.

Derrick, W.T.C., 2020. "Perceptions and Attitudes towards Micro E-Scooters in Singapore." Retrieved September 5, 2021(https://open-education repository.ucl.ac.uk/681/1/Wee%2C%20Derrick.pdf).

Dill, J., McNeil, N., 2021. Are shared vehicles shared by all? A review of equity and vehicle sharing. J. Plan. Lit. 36 (1), 5–30. https://doi.org/10.1177/0885412220966732/ASSET/IMAGES/LARGE/10.1177_0885412220966732-FIG1.JPEG.

Duran-Rodas, D., Wright, B., Pereira, F.C., Wulfhorst, G., 2021. Demand and/or equity (DARE) method for planning bike-sharing. Transp. Res. Part D: Transp. Environ. 97, 102914. https://doi.org/10.1016/J.TRD.2021.102914.

Eriksson, L., Forward, S.E., 2011. Is the intention to travel in a pro-environmental manner and the intention to use the car determined by different factors? Transp. Res. Part D: Transp. Environ. 16 (5), 372–436. https://doi.org/10.1016/j.trd.2011.02.003.

Fitch-Polse, D.T., Mohiuddin, H., Handy, S.L., 2024. Can bike-share change attitudes? evidence from the sacramento, California Region. Transp. Lett. https://doi.org/10.1080/19427867.2024.2360336.

Fitch, D.T., Carlen, J., Handy, S.L., 2022. What makes bicyclists comfortable? Insights from a visual preference survey of casual and prospective bicyclists. Transp. Res. A Policy Pract. 155, 434–449. https://doi.org/10.1016/j.tra.2021.11.008.

Fitch, D.T., Mohiuddin, H., Handy, S.L., 2021. Examining the Effects of the Sacramento Dockless E-Bike Share on Bicycling and Driving. Sustain. (Switzerland). https://doi.org/10.3390/su13010368.

Fitt, H., Curl, A., 2020. The early days of shared micromobility: a social practices approach. J. Transp. Geogr. 86, 102779. https://doi.org/10.1016/j.jtrangeo.2020.102779.

Franckle, R.L., Dunn, C.G., Vercammen, K.A., Dai, J., Soto, M.J., Bleich, S.N., 2020. Facilitators and barriers to bikeshare use among users and non-users in a socioeconomically diverse urban population. Prev. Med. Rep. 20, 101185. https://doi.org/10.1016/J.PMEDR.2020.101185.

Fukushige, T., Fitch, D.T., Handy, S., 2021. Factors influencing dock-less E-bike-share mode substitution: evidence from Sacramento, California. Transp. Res. Part D: Transp. Environ. 99, 102990. https://doi.org/10.1016/J.TRD.2021.102990.

Fuller, D., Gauvin, L., Kestens, Y., Daniel, M., Fournier, M., Morency, P., Drouin, L., 2011. Use of a new public bicycle share program in Montreal, Canada. Am. J. Prev. Med. 41 (1), 80–83. https://doi.org/10.1016/j.amepre.2011.03.002.

Garrard, J., Handy, S.L., Dill, J., 2012. Women and Cycling. in City Cycling.

Geus, D.e., Bas, I.D., Bourdeaudhuij, C.J., Meeusen, R., 2008. Psychosocial and environmental factors associated with cycling for transport among a working population. Health Educ. Res. https://doi.org/10.1093/her/cym055.

Grasso, S.H., Barnes, P., Chavis, C., 2020. Bike share equity for underrepresented groups: analyzing barriers to system usage in Baltimore, Maryland. Sustain. (Switzerland) 12 (18). https://doi.org/10.3390/su12187600.

Handy, S., Lee, A.E., 2020. What is it about bicycling? Evidence from Davis, California. Travel behaviour and society 20, 348–357. https://doi.org/10.1016/j.tbs.2020.05.001.

Handy, S.L., Xing, Y., Buehler, T.J., 2010. Factors associated with bicycle ownership and use: a study of six small U.S. Cities. Transportation 37 (6), 967–985. https://doi.org/10.1007/s11116-010-9269-x.

Hazen, B.T., Overstreet, R.E., Wang, Y., 2015. Predicting public bicycle adoption using the technology acceptance model. Sustain. (Switzerland) 7 (11), 14558–14573. https://doi.org/10.3390/su71114558.

Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32, 100170. https://doi.org/10.1016/j.jocm.2019.100170.

Fitt, H., Curl, A., 2019. *E-Scooter Use in New Zealand: Insights around Some Frequently Asked Questions*. doi:10.13140/RG.2.2.13510.93761.

Hess, S., Palma, D., 2023. “Apollo: A Flexible, Powerful and Customisable Freeware Package for Choice Model Estimation and Application Version 0.2.9 User Manual.”.

Hirsch, J.A., Stewart, I., Ziegler, S., Richter, B., Mooney, S.J., 2019. Residents in Seattle, WA report differential use of free-floating Bikeshare by Age, Gender, race, and Location. Front. Built Environ. 17. https://doi.org/10.3389/FBUIL.2019.00017.

Hoe, N., 2015. Bike Sharing in Low-Income Communities: Perceptions and Knowledge. Institute for Survey Research, Temple University, Philadelphia, PA.

Hoerler, R., Tomic, U., Dijk, J.V., Patt, A., Duce, A.D., 2020. Are Carsharing Users More Likely to Buy a Battery Electric, Plug-in Hybrid Electric or Hybrid Electric Vehicle? Powertrain Choice and Shared Mobility in Switzerland. In: *2020 Forum on Integrated and Sustainable Transportation Systems, FISTS 2020*. Institute of Electrical and Electronics Engineers Inc, pp. 70–76.

Hyun (Kyung), K., Naz, F., Cronley, C., Leat, S., 2021. User characteristics of shared-mobility: a comparative analysis of car-sharing and ride-hailing services. Transp. Plan. Technol. 1–12. https://doi.org/10.1080/03081060.2021.1919351.

James, O., Swiderski, J., Hicks, J., Teoman, D., Buehler, R., 2019. Pedestrians and E-scooters: an initial look at E-scooter parking and perceptions by riders and non-riders. Sustainability 11 (20), 5591. https://doi.org/10.3390/su11205591.

Kabra, A., Belavina, E., Girotra, K., 2019. Bike-share systems: accessibility and availability. Manag. Sci. https://doi.org/10.1287/mnsc.2019.3407.

Kellstedt, D., Spengler, J.O., Bradley, K., Maddock, J.E., 2019. Evaluation of free-floating bike-share on a university campus using a multi-method approach. Prev. Med. Rep. 16, 100981. https://doi.org/10.1016/j.pmedr.2019.100981.

Kim, B., Kim, D., 2020. Exploring the key antecedents influencing consumer’s continuance intention toward bike-sharing services: focus on China. Int. J. Environ. Res. Public Health 17 (12), 1–14. https://doi.org/10.3390/ijerph17124556.

Kim, S.H., Park, H.J., 2011. Effects of social influence on consumers’ voluntary adoption of innovations prompted by others. J. Bus. Res. 64 (11), 1190–2114. https://doi.org/10.1016/j.jbusres.2011.06.021.

Kitamura, R., Mokhtarian, P.L., Laidet, L., 1997. A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area. Transportation 24 (2), 125–158. https://doi.org/10.1023/A:1017959825565.

Kjærup, M., Skov, M.B., van Berkel, N., 2021. E-Scooter Sustainability – A Clash of Needs, Perspectives, and Experiences. In: Ardito, C., et al. Human-Computer Interaction – INTERACT 2021. INTERACT 2021. Lecture Notes in Computer Science, vol 12934. Springer, Cham. https://doi.org/10.1007/978-3-030-85613-7_26.

Kroesen, M., Handy, S., Chorus, C., 2017. Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. Transp. Res. A Policy Pract. 101, 190–202. https://doi.org/10.1016/j.tra.2017.05.013.

Li, Q., Luca, D., Fuerst, F., Wei, Z., 2024. Success in Tandem? The impact of the introduction of e-bike sharing on bike sharing usage. Res. Transp. Econ. 107, 1–8. https://doi.org/10.1016/j.retrec.2024.101476.

Ma, L., Dill, J., 2015. Associations between the objective and perceived built environment and bicycling for transportation. J. Transp. Health 2 (2), 248–255. https://doi.org/10.1016/j.jth.2015.03.002.

McNeil, N., Broach, J., Dill, J., 2018. Breaking barriers to bike share: lessons on bike share equity. ITE J. (Inst. Transp. Eng.) 88 (2), 31–35.

Mitra, S.K., Bae, Y., Ritchie, S.G., 2019. Use of ride-hailing services among older adults in the United States. Transp. Res. Rec.: J. Transp. Res. Board 2673 (3), 700–710. https://doi.org/10.1177/0361198119835511.

Mohiuddin, H., 2021. Planning for the first and last mile: a review of practices at selected transit agencies in the United States. Sustain. (Switzerland) 13 (4), 1–19. https://doi.org/10.3390/su13042222.

Mohiuddin, H., Fitch-Polse, D.T., Handy, S.L., 2023. Does bike-share enhance transport equity? Evidence from the Sacramento, California Region. J. Transp. Geogr. 109, 103588. https://doi.org/10.1016/J.JTRANGEO.2023.103588.

Mohiuddin, H., Fukushige, T., Fitch-Polse, D.T., Handy, S.L., 2024. Does dockless bike-share influence transit use? Evidence from the Sacramento Region. Int. J. Sustain. Transp. 18 (2), 146–167. https://doi.org/10.1080/15568318.2023.2252757.

Mooney, S.J., Hosford, K., Howe, B., Yan, A.n., Winters, M., Bassok, A., Hirsch, J.A., 2019. Freedom from the station: spatial equity in access to dockless bike share. J. Transp. Geogr. 74, 91. https://doi.org/10.1016/J.JTRANGEO.2018.11.009.

NACTO. 2023. “157 Million Trips.” Retrieved August 6, 2024 (https://nacto.org/publication/shared-micromobility-report-2023/).

National Association of City Transportation Officials. 2020. “Shared Micromobility in the U.S.: 2019.” Retrieved October 11, 2020 (https://nacto.org/shared-micromobility-2019/).

Nikiforiadis, A., Paschalidis, E., Stamatiadis, N., Raptopoulou, A., Kostareli, A., Basbas, S., 2021. Analysis of attitudes and engagement of shared E-scooter users. Transp. Res. Part D: Transp. Environ. 94, 102790. https://doi.org/10.1016/j.trd.2021.102790.

Petzoldt, T., Ringhand, M., Anke, J., Schekatz, N., 2021. Do German (Non)Users of E-Scooters Know the Rules (and Do They Agree with Them)?” *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in*. Bioinformatics) 12791 (pp), 425–435. https://doi.org/10.1007/978-3-030-78358-7_29.

Phithakkitnukoon, S., Sukhvibul, T., Demissie, M., Smoreda, Z., Natwichai, J., Bento, C., 2017. Inferring social influence in transport mode choice using mobile phone data. EPJ Data Sci. 6 (1). https://doi.org/10.1140/epjds/s13688-017-0108-6.

Pike, S., Lubell, M., 2018. The conditional effects of social influence in transportation mode choice. Res. Transp. Econ. 68 (August), 2–10. https://doi.org/10.1016/j.retrec.2018.05.010.

Qian, X., Jaller, M., Niemeier, D., 2020. Enhancing equitable service level: which can address better, dockless or dock-based bikeshare systems? J. Transp. Geogr. 86, 102784. https://doi.org/10.1016/J.JTRANGEO.2020.102784.

Reck, D.J., Axhausen, K.W., 2021. Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland. Transp. Res. Part D: Transp. Environ. 94 (April), 102803. https://doi.org/10.1016/j.trd.2021.102803.

Sanders, R.L., Branion-Calles, M., Nelson, T.A., 2020. To scoot or not to scoot: Findings from a recent Survey about the benefits and barriers of using E-scooters for riders and non-riders. Transp. Res. A Policy Pract. 139, 217–227. https://doi.org/10.1016/j.tra.2020.07.009.

Shaheen, S.A., Zhang, H.a., Martin, E., Guzman, S., 2011. China's Hangzhou Public Bicycle. Transp. Res. Rec.: J. Transp. Res. Board 2247 (1), 33–41. https://doi.org/10.3141/2247-05.

Sikder, S., 2019. Who uses ride-hailing services in the United States? Transp. Res. Rec. https://doi.org/10.1177/0361198119859302.

Smith, A., 2016. "Who in America Uses Ride-Hailing Apps like Uber or Lyft | Pew Research Center." *Pew Research Center*. Retrieved May 4, 2021 (https://www.pewresearch.org/internet/2016/05/19/on-demand-ride-hailing-apps/).

Stromberg, J., 2015. "Bike Share Users Are Mostly Rich and White. Here's Why That's Hard to Change" Retrieved June 20, 2022(https://www.vox.com/2015/5/15/8608567/bike-share-wealth-race).

Shaheen, S.A., Martin, E.W., Chan, N.D., Cohen, A.P., Pogodzinski, M., 2014. Public Bikesharing in North America during a period of rapid expansion: understanding business models, industry trends and user impact. MTI Report 12–29.

Tang, Y., Pan, H., Shen, Q., 2011. Bike-Sharing Systems in Beijing, Shanghai, and Hangzhou and Their Impact on Travel Behavior.

Treviño, J., 2019. E-bikes take the lead in city bikeshare programs. Retrieved December 13, 2022 (https://www.usnews.com/news/cities/articles/2019-08-12/e-bikes-take-the-lead-in-city-bikeshare-programs#:~:text=As%20of%20early%20August%2C%2041,including%20a%20jump%20in%20ridership.).

US Census Bureau. 2021. "U.S. Census Bureau QuickFacts: Davis City, California." Retrieved July 16, 2022 (https://www.census.gov/quickfacts/daviscitycalifornia).

Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. Transp. Res. B Methodol. 90, 192–217. https://doi.org/10.1016/j.trb.2016.04.021.

Wang, D., Li, Z., Xiao, B., 2019. Social influence in first-time and upgrade adoption. Electron. Commer. Res. Appl. 34, 1–8. https://doi.org/10.1016/j.elerap.2019.100834.

Wang, H., Dong, Y., Ma, L., 2024. Determinants of dockless bicycle-sharing adoption and usage intensity for commuting and errands: evidence from disadvantaged neighborhoods. Land 13 (12). https://doi.org/10.3390/land13122055.

Willis, D.P., Manaugh, K., El-Geneidy, A., 2015. Cycling under influence: summarizing the influence of perceptions, attitudes, habits, and social environments on cycling for transportation. Int. J. Sustain. Transp. 9 (8), 565–579.

Yang, Y., Sloate, E., Khadem, N., Chavis, C., Frías-Martínez, V., 2024. "Comparing E-bike and conventional bicycle use patterns in a public bike share system: a case study of richmond VA. J. Cycling Micromobility Res. 2, 100023. https://doi.org/10.1016/j.jcmr.2024.100023.

Yu, Ying, Wenjie Yi, Yuanyue Feng, and Jia Liu. 2018. "Understanding the Intention to Use Commercial Bike-Sharing Systems: An Integration of TAM and TPB." in *Proceedings of the 51st Hawaii International Conference on System Sciences*.

Zhu, M., Hu, X., Lin, Z., Li, J., Wang, S., Wang, C., 2020. Intention to Adopt Bicycle-Sharing in China: Introducing Environmental Concern into the Theory of Planned Behavior Model. https://doi.org/10.1007/s11356-020-10135-1.