Transportation
https://doi.org/10.1007/s11116-021-10235-y

The determinants of shared bike use in China

Yiling Deng[1] · **Pengjun Zhao**[2,3]

Accepted: 18 September 2021
© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2021

Abstract

Free-floating bike share (FBS) represents a new generation of bike share schemes and provides mobility opportunities that influence people's daily travel. Understanding the determinants of FBS use can provide a basis for the further development of bike share programs and support related policymaking. Previous studies have used survey data with rather small samples and have focused only on FBS users while ignoring nonusers. The influences of information and communication technology (ICT) use and social context are under-researched. By using a dataset that is nationally representative of the potential users of FBS in China, this study applied a two-stage Bayesian multilevel hurdle model to investigate participation in and the corresponding usage of FBS. The independent variables include sociodemographics, ICT use, travel characteristics, physical environment, and social context. We found that ICT use has a significant effect on both participation in and the usage of FBS, social context only has a significant effect on participation in FBS, and age and annual individual income have nonlinear effects on the usage of FBS. This study provides policymakers and FBS operators with suggestions for promoting FBS use.

Keywords Free-floating bike share · Two-stage Bayesian multilevel hurdle model · China household finance survey · Social context · Nonlinear

Introduction

The concept of bike share has been around since the 1960s. Its development has gone through the failure of the first and second generations of bike share to the global popularity of the third generation of bike share (DeMaio 2009). Before 2016, the term bike share usually referred to the provision of bikes to enable short-term rental between

✉ Yiling Deng
yiling@zjut.edu.cn

Pengjun Zhao
pengjun.zhao@pku.edu.cn

1 School of Design and Architecture, Zhejiang University of Technology, Hangzhou 310023, Zhejiang Province, China

2 College of Urban and Environmental Sciences, Peking University, Beijing 100871, China

3 School of Urban Planning and Design, Peking University Shenzhen Graduate School, Shenzhen 518055, China

docking stations (i.e., the third generation of bike share or station-based bike share (SBS)) (Chen et al. 2020b). In recent years, bike share has continued to evolve, first with the advent of free-floating bike share (FBS) systems and then with the inclusion of free-floating e-scooter share systems (Teixeira et al. 2021). The most important feature that distinguishes FBS programs from their predecessors is the elimination of fixed parking stations and docks. Shared bikes can be picked up and dropped off at any open space in a city. From the user's perspective, FBS provides a more convenient and flexible option for accessing shared bikes than SBS, changing the way people move around cities. From a city management perspective, FBS creates new mobility opportunities and contributes to easing traffic congestion, reducing air pollution and fuel usage, and integrating physical activity into daily life (Hirsch et al. 2019).

Along with the increase in the number of FBS program, the relevant studies are emerging (Chen et al. 2020b). These studies have investigated the sociodemographics of FBS users (Du and Cheng 2018; Li et al. 2018; Chen et al. 2020a; Link et al. 2020) and the spatiotemporal patterns of FBS use (Shen et al. 2018; Du et al. 2019; Li et al. 2020). These studies have shown that FBS is more popular among young or middle-aged groups (Du and Cheng 2018; Li et al. 2018), and a higher rate of FBS use is associated with a more supportive environment for cycling (Shen et al. 2018; Tu et al. 2019). However, the samples of these studies were rather small and included only FBS users while ignoring nonusers. Most conclusions were drawn from the descriptive statistical analysis without using statistical models and considering the correlation of explanatory variables. In addition, the effects of information and communication technology (ICT) use and social context have on FBS use remain under-researched.

Investigating the determinants of FBS use can provide a reference basis for its development and support for related policymaking. To conduct an in-depth study of the determinants of FBS use, two questions should be answered: First, why do some people participate in FBS, while others do not or have never heard of FBS during the reference period? Second, once a decision to participate in FBS has been made, what motivates some people to use FBS more often than others during the given period? As Chen et al. (2020b) note, studies exploring these two questions are extremely limited and the results are not unanimous. More studies addressing these issues can help extend the limited knowledge about FBS users and their usage patterns as well as the underlying mechanisms affecting their usage.

This study aims to answer these two questions and to improve the understanding of the determinants of FBS use. This study differs from prior research in the following ways: (i) We used a large dataset with a national representation of the potential users of FBS in China. The dataset not only contains information regarding the characteristics of FBS users but also includes the characteristics of people who do not participate or have never heard of FBS. (ii) We employed a two-stage multilevel hurdle model to explore the determinants of FBS use by differentiating between the two questions. (iii) We included the variables of ICT use and social context.

The remainder of the paper is organized as follows. Literature review section reviews previous studies regarding FBS. Data and methodology section describes the dataset and variables and introduces the methodology. Results and discussion section presents and discusses the empirical results. Conclusions section concludes the paper.

Literature review

The literature on bike share has mainly focused on SBS. A large spectrum of issues associated with SBS, including user demographics and preferences, usage rates and geospatial visualizations, safety, redistribution options, and technological innovation, has been examined (Fishman 2016). Despite the partial similarities between FBS and SBS, the distinctive characteristics of FBS may result in different outcomes, especially in travel behavior and its determinants, and these different outcomes need to be further studied. In this section, only FBS studies on this topic are reviewed.

The sociodemographics of FBS users have become a common focus of FBS operators and researchers. Some industry reports published by FBS operators have revealed the sociodemographics of their users. In Mobike's report, a balanced gender distribution (49% females vs. 51% males) and young age distribution (20–40 years old) were found in the analysis of 200 million users in China's major cities (How cycling changes cities: insights on how bikesharing supports urban development 2018). According to an Ofo report, the gender distribution of its users was 43% females and 57% males, and the users were mainly between the ages of 18 and 45 years old (Cycling report of major cities in China 2017 Q4 2018). In FBS operators' reports, users' sociodemographics are limited to gender and age since other characteristics, such as education level and employment sector are not recorded in users' registration information. Little academic research has recovered FBS users' sociodemographics. Some studies suggested that most FBS users were younger, with a high education level (Li et al. 2018; Xin et al. 2018; Sun 2018). Regarding occupation, company employees and university students were the main FBS users (Du and Cheng 2018; Li et al. 2018; Xin et al. 2018). Other studies explored both similarities and differences between SBS and FBS users. Chen et al. (2020a) suggested that SBS and FBS had similar user structures, but different factors influenced their use frequency. Link et al. (2020) suggested that the reasons that users tried FBS were similar to the reasons that users tried SBS. In addition to the sociodemographics, studies have shown that ICT usage, such as mobile internet usage (Chen et al. 2020a); travel characteristics, such as the commuting distance (Sun 2018); and subjective factors, such as attitudes and satisfaction with system features (Link et al. 2020), also influence an individual's propensity to participate in FBS.

Existing studies have examined the usage of FBS by examining the effects of the built environment. Employment, population, land-use mix, access to public transit, cycling facilities, and proximity to a center location significantly impact FBS use (Shen et al. 2018; Guidon et al. 2020, 2019). Due to the flexibility of FBS in terms of riding and parking, the study unit of FBS is the grid cells across the city, while the study unit of SBS is the perimeter of the stations. However, as Tu et al. (2019) showed, the relationships between FBS trip density and various factors were broadly consistent with existing SBS studies.

Although several studies have assessed the relationship between various factors and FBS use, these studies are limited in the following ways. First, a variety of user sociodemographics was questioned in FBS research surveys, but their samples were rather small (usually several hundred people) and only included FBS users. Most conclusions were drawn from a descriptive statistical analysis. Taking income as an example, Du and Cheng (2018) suggested that people with average and below average income were the main users; Xin et al. (2018) suggested that the main users were those with an average income; Sun (2018) suggested that users had various income levels (44% were below average and 41% were above average) apart from the no income group (15%). The main reason for these inconsistent results is that some groups of people are overrepresented in the surveyed samples.

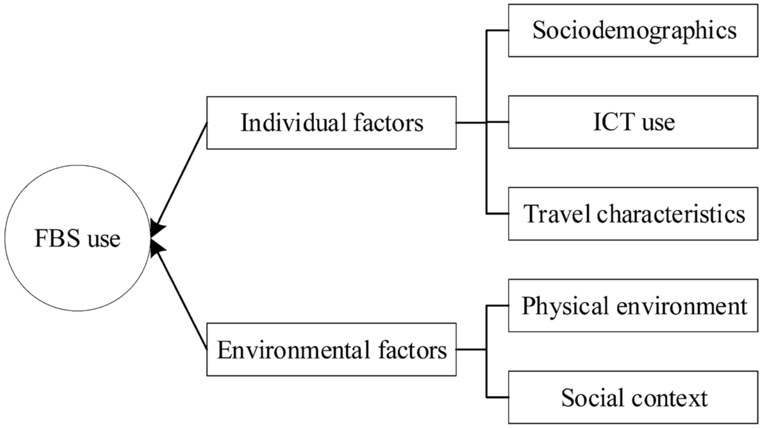

Fig. 1 Conceptual framework

In addition, since explanatory variables are correlated, the actual impact of each variable can only be computed on an "all other things being equal" basis by using statistical models. Second, the effects of social context and ICT use on FBS use are under-researched. For cycling, Handy et al. (2010) and Xing et al. (2010) found that individuals' social context had a strong influence on the use of bikes for transportation and recreation. Heinen et al. (2011) found that social support from family or friends significantly influenced individuals' decision to cycle for short trips. Does the impact of the social context on cycling still hold for FBS use? Although Chen et al. (2020a) found that people with the largest data packages were more likely to be frequent FBS users, do other ICT use variables, such as ICT usage history and expenditures, influence FBS use? Third, the existing studies were focused on a single region and thus lack external validity.

This study attempts to address related issues and enhance the understanding of the underlying mechanisms of FBS use. From the literature, we proposed a conceptual framework, as shown in Fig. 1. The framework distinguishes two categories of determinants constituting the options to influence FBS use. The first category of determinants is individual characteristics, including sociodemographics, ICT use, and travel characteristics. The second category of determinants is the environment, which encompasses the physical environment and the social context. We then applied a two-stage Bayesian multilevel hurdle model based on a large dataset including both FBS users and nonusers to reveal the influences of these determinants.

Data and methodology

Data

China has the world's largest FBS market, with a total fleet size that grew from 2 million in 2016 to 23 million in 2017, covering over 200 cities (Gu et al. 2019). The data used for this study were obtained from the China Household Finance Survey (CHFS) conducted by the Survey and Research Center for China Household Finance of the Southwestern University of Finance and Economics. CHFS was conducted by face-to-face interviews by using standardized questionnaires, and covered 29 mainland provinces and municipalities; a multistage cluster and a stratified probability sampling strategy were used to ensure national representativeness (Gan et al. 2014). For each household, the individual with the most knowledge of the family's economic situation was selected to complete the questionnaire. Four waves of CHFS were performed in 2011, 2013, 2015, and 2017. The survey collected detailed household information, including demographics, assets and debts, insurance and security, expenditure and income, and financial knowledge and subjective evaluation.

We employed the 2017 wave of CHFS, in which 40,011 households (127,012 individuals) from 1428 communities and villages in 355 counties were interviewed. By random assignment, two slightly different questionnaires were used for the 2017 wave of CHFS. Approximately half of the households completed questionnaire A and the other half completed questionnaire B. Questionnaire A and questionnaire B differ in the setting of some questions to cover more issues, but not to increase the number of questions an individual needs to answer. The respondents who completed questionnaire B on behalf of their households and answered yes to the question "Do you use a smartphone" were asked questions about FBS use. After removing respondents who were not asked the FBS use-related questions and those that were missing values for any of the independent variables, the resulting sample consisted of 8,272 individuals in 331 counties of 161 cities of 29 mainland provinces and municipalities. There were demographic differences between the resulting sample and the original CHFS data. The resulting sample was similar to the original CHFS data in terms of gender but had higher proportions of younger people and people with higher levels of education and income. This bias is mainly a result of the demographic characteristics of the smartphone user population. Since the use of a smartphone is a prerequisite for using FBS, in the areas examined, the resulting sample represents potential users of FBS (including both users and nonusers) in China. Among 8272 individuals, 1,135 individuals made at least one FBS trip during the reference period. Table 1 presents the characteristics of the resulting sample and the three subsamples.

Variables

In the expenditure and income section of the 2017 wave of CHFS, several questions about FBS use, such as riding frequency, average riding time, and FBS brand preference were asked. Two questions were adopted as dependent variables. The first one was "Within the past week, have you used an FBS?" (a discrete variable whose reference is "no", with two alternative answers, "yes" and "never heard of"). The "no" category is the intermediate category of the three categories. Using the "no" category rather than the "never heard of" category as the reference category allows for the identification of coefficient differences between the "yes" and "no" categories, thus facilitating comparison with previous studies. The second question was "Within the past week, how many times have you used an FBS?" (a continuous variable that only includes the "yes" group). For later convenience, these two dependent variables are abbreviated as participation in FBS and the usage of FBS. In this sample, the shares of the responses to the FBS participation question were as follows: 13.9% never heard of, 72.4% no, and 13.7% yes. The "yes" category (i.e., the FBS trip makers) made 5.24 FBS trips weekly on average.

The independent variables captured two dimensions, namely, individual characteristics and environmental factors, which further comprised sociodemographics, ICT use, travel characteristics, physical environment, and social context. The sociodemographics included gender, age, education level, employment status, annual individual income,

Table 1 Descriptive statistics of the variables

Variable	Mean (St. dev)/Proportion			
	Full Sample	Subsample of "Yes"	Subsample of "No"	Subsample of "Never heard of"
Dependent variables				
Have you used an FBS within the past week?				
Yes	13.7%			
No	72.4%			
Never heard of it	13.9%			
How many times have you used an FBS within the past week?		5.24 (5.15)		
Sociodemographics				
Gender				
Female	46.1%	49.6%	46.2%	41.8%
Male	53.9%	50.4%	53.8%	58.2%
Age	47.51 (14.22)	38.76 (12.71)	48.40 (14.28)	51.55 (11.74)
Education level	4.31 (1.72)	5.51 (1.65)	4.30 (1.67)	3.20 (1.21)
Employment status				
Office worker	26.6%	47.4%	25.7%	8.1%
Manufacturing worker	4.4%	2.7%	4.3%	6.5%
Service worker	8.1%	7.0%	8.3%	10.7%
Other worker	13.9%	10.0%	12.5%	24.8%
Employer	6.1%	6.7%	6.3%	4.9%
Student	2.2%	5.0%	2.0%	0.3%
Retired	21.2%	10.5%	24.0%	17.6%
Unemployed	17.5%	10.7%	16.9%	27.1%
Annual individual income (in 100,000 Yuan)	0.23 (0.46)	0.49 (0.68)	0.21 (0.43)	0.09 (0.18)
Annual household income (in 100,000 Yuan)	0.57 (0.92)	1.03 (1.20)	0.53 (0.90)	0.31 ()

Table 1 (continued)

Variable	Mean (St. dev)/Proportion			
	Full Sample	Subsample of "Yes"	Subsample of "No"	Subsample of "Never heard of"
Marital status				
Single	17.0%	27.4%	15.8%	13.3%
Married or cohabitating	83.0%	72.6%	84.2%	86.7%
Household head				
Yes	59.6%	63.4%	59.4%	56.9%
No	40.4%	36.6%	40.6%	43.1%
Household size	3.09 (1.32)	2.91 (1.20)	3.08 (1.29)	3.30 (1.53)
ICT use				
Monthly household phone bill (in 100 Yuan)	2.52 (3.32)	3.26 (3.97)	2.47 (3.27)	2.04 (2.76)
Years of using smartphones	5.05 (3.78)	6.89 (3.69)	5.02 (3.75)	3.37 (3.17)
Travel characteristics				
Commuting mode				
Bus	7.7%	16.6%	7.0%	3.0%
Rail Transit	2.3%	10.6%	1.2%	0.1%
Official car or bus	2.4%	3.9%	2.2%	1.9%
Private car	7.5%	11.4%	7.7%	2.2%
Taxi	1.0%	3.0%	0.7%	0.3%
E-bike or motorbike	10.6%	7.8%	11.0%	11.7%
Bike	5.2%	12.5%	4.3%	2.5%
Walking	10.5%	12.1%	10.5%	8.8%
None	58.3%	39.2%	59.5%	71.1%
Household car ownership	0.41 (0.59)	0.59 (0.67)	0.41 (0.59)	0.24 (0.47)

Table 1 (continued)

Variable	Mean (St. dev)/Proportion			
	Full Sample	Subsample of "Yes"	Subsample of "No"	Subsample of "Never heard of"
Physical environment				
Living environment				
City downtown	58.3%	82.8%	59.4%	28.2%
City suburb	11.0%	9.7%	11.5%	9.5%
Large town	2.7%	2.1%	2.9%	2.7%
Small town	12.7%	2.1%	12.5%	24.2%
Countryside/village	15.3%	3.3%	13.7%	35.3%
House type				
Rented	15.1%	25.9%	14.0%	9.9%
Self-owned/free	84.9%	74.1%	86.0%	90.1%
Social context				
Household members' commuting mode (Social support and modeling)				
Bus	12.7%	15.6%	12.7%	10.0%
Rail transit	4.3%	9.5%	3.9%	1.0%
Official car or bus	3.7%	4.5%	3.8%	2.8%
Private car	12.7%	17.8%	12.8%	7.0%
Taxi	1.6%	2.9%	1.5%	1.1%
E-bike or motorbike	14.3%	9.8%	14.6%	17.5%
Bike	5.5%	8.7%	5.2%	3.9%
Walking	12.1%	9.0%	11.7%	17.0%
None	47.8%	41.4%	48.1%	52.7%
Social trust	2.20 (0.90)	2.51 (0.84)	2.19 (0.89)	1.90 (0.88)
Number of observations	8272	1135	5990	1147

annual household income, marital status, household head, and household size. ICT use included monthly household phone bill and years of using smartphones. The travel characteristics included the commuting mode and household car ownership. These variables were processed as follows: the education level variable had nine choices (i.e., never attended school, primary school, secondary school, high school, polytechnic, junior college, university undergraduate, master's, and doctorate) that were converted into a continuous variable ranging from 1 to 9. The employment status variable had eleven choices (i.e., manager, technician, clerk, manufacturing, service, farmer, other worker, employer, student, retired, unemployed) that were merged into seven choices (i.e., office worker, manufacturing worker, service worker, other worker, employer, student, retired, unemployed) and were taken as a nominal variable. The marital status variable had seven choices (i.e., unmarried, married, cohabitating, separated, divorced, widowed, and remarried) that were merged into two choices (i.e., single and married or cohabitating) and were treated as a nominal variable. The commuting mode variable had eight choices (i.e., bus, rail transit, official car or bus, private car, taxi, E-bike or motorcycle, bike, and walking). The respondents could choose one or more modes as their major commuting modes. The reason for choosing more than one main mode could be that they used different commuting modes on different days or used one mode as a feeder to another. Although we cannot distinguish between these two possibilities, we only needed to capture the effect of whether a mode was chosen by respondents or their household members as their commuting mode on FBS use. Note that 58.3% of respondents did not choose any commuting mode for two reasons: some had an employment status of retired, unemployed, or other worker (e.g., live-in nanny) who did not need to commute; and some had an employment status of employer or student who needed to commute but were not asked about their commuting modes in CHFS, so their commuting modes were missing. Taking no commuting mode choice as the reference, we converted respondents' commuting mode choices into eight dummy variables. Because some respondents chose more than one mode, while others who did not commute did not choose any mode, the sum of the probabilities of all the modes was not equal to 100%. The gender and household head variables were directly treated as nominal variables. The age, annual individual income, annual household income, household size, household car ownership, monthly household phone bill, and years of using smartphones variables were directly treated as continuous variables. Because the effects of age and annual individual income were expected to be nonlinear parameters, quadratic terms for these variables were included to account for higher-order effects.

The physical environment included the living environment and house type, which were directly treated as nominal variables. Since individuals are either unaware of the degree to which they are socially affected or rarely acknowledge it, directly asking interviewees how influential their social context is would be unlikely to yield a useful answer (Nolan et al. 2008). We tried to indirectly measure social context in two dimensions. The first dimension was social support and modeling. Titze (2008) used two items—"household members frequently use cycling for transportation" and "household members encourage me to use cycling for transportation" to represent the effect of social support and modeling from household members on the use of cycling. Following this approach, social support and modeling were measured by the major commuting modes of the other household members in this study. For workers and students, commuting accounted for the highest proportion of all trip purposes. Although the commuting mode choice may be constrained by many factors, such as car ownership and transportation mode availability, it largely reflects people's attitude toward the transportation mode they choose (Van et al. 2014). The choices of the household members' commuting mode had social support and modeling effects on individuals' use of FBS. We speculate that individuals would be more likely to use FBS if household members commute by bike or public transit. However, this assumption requires further verification. In addition, whether household members' commuting by walking, private cars, or E-bikes has an impact on individuals' use of FBS is unclear. The survey asked about the major commuting modes of other household members, which was converted into eight continuous variables, representing the counts of other household members choosing these modes as their major commuting mode. We used proportions to describe the household member's commuting modes in Table 1 by convention, although they were treated as continuous variables. Note that 47.8% of respondents have no household members living together or have no household members who need to commute to work. The second dimension was social trust. Social trust is a critical factor in relationships between individuals and between individuals and organizations (Nyhan 2000). FBS as a collaborative consumption may require a degree of trust in other strangers (e.g., trusting that other strangers will take good care of the bikes to ensure good service quality). The survey asked whether the respondent trusts strangers, and the respondents answered by using a five-point Likert scale, which was converted to a continuous variable from 1 to 5 (very untrusting = 1, untrusting = 2, fair = 3, trusting = 4, very trusting = 5).

Methodology

Two dependent variables were hierarchical, with the usage of FBS nested within participation in FBS, which naturally forms a two-stage decision-making structure. One solution to model this decision-making structure is the two-stage hurdle model, which was proposed by Mullahy (1986). Another reason for using the two-stage hurdle model is that the decision to participate in FBS may be affected by factors that are different from those affecting the decision to use FBS. The two-stage hurdle model combines a binary model that models whether or not to participate with a zero-truncated Poisson model that models the level of participation of these participants. The probability function of this basic model can be written as:

$$\Pr\{Y = y\} = \begin{cases} \pi, \quad y = 0, \\ \dfrac{(1-\pi)\mu^y e^{-\mu}}{y!}, \quad y = 1, 2, \ldots \end{cases} \tag{1}$$

where μ is the parameter of the Poisson distribution.

In this study, we extended the basic two-stage hurdle model in three ways. First, a multinomial logit (MNL) model and a zero-truncated negative binomial (NB) model were used instead of the binary model and the zero-truncated Poisson model based on the nature of the data. Stage 1 categorizes individuals as follows: individuals who have never heard of FBS; individuals who have not participated in FBS within the past week; individuals who have participated in FBS within the past week. The MNL model is ordinally used. Stage 2 estimates the usage of FBS by individuals who have participated in FBS within the past week. Either the zero-truncated Poisson model or the zero-truncated NB model can be used. These two models make different assumptions about the distribution of the dependent variable. The prerequisite for employing the Poisson model is that the variance $Var(Y)$ is equal to the mean $E(Y)$: $Var(Y) = E(Y) = \mu$. The NB model is preferable to the Poisson model if the dependent variable is overdispersed, implying that the variance of the count is greater than the mean. An overdispersion test is often used to test the assumption that $Var(Y) = \mu + \alpha * f(\mu)$, where a dispersion factor $\alpha < 0$ indicates underdispersion and $\alpha > 0$ indicates overdispersion. $f(.)$ is a monotone function (usually linear or quadratic). The resulting test is equivalent to test H_0: $\alpha = 0$ versus H_1: $\alpha \neq 0$. The t statistic of asymptotic standard normality under the null is used as the test statistic (Cameron and Trivedi 1990). For our data, the dispersion factor α is 3.47, which indicates significant overdispersion and strongly favors the zero-truncated NB model. The probability function of this model is as follows:

$$\Pr\left\{Y_1 = y_1, Y_2 = y_2\right\} = \left\{ \begin{array}{l} \pi_1, y_1 = \textit{never heard} \wedge y_2 = 0, \\ \pi_2, y_1 = \textit{no} \wedge y_2 = 0, \\ \left(1 - \pi_1 - \pi_2\right) \frac{\mu}{1-(1+\alpha\mu)^{-1/\alpha}}, y_1 = \textit{yes} \wedge y_2 = 1, 2, \ldots \end{array} \right\} \quad (2)$$

where μ is the mean parameter and α is the overdispersion parameter of the NB distribution.

Second, we incorporated a multilevel framework into the two-stage hurdle model to capture correlations that arise due to the hierarchical data structure (i.e., individuals nested in counties, nested in cities). Previous studies have suggested that the county- and city-specific characteristics such as the quantity and quality of FBS services affect the FBS use (Chen et al. 2020b; Gu et al. 2019). Varying intercept models were employed to capture the variance between counties and cities. We calculated an intraclass correlation coefficient (ICC), which refers to the proportion of total variance in the outcome attributed to the county level and city level. The ICC is calculated as follows: $ICC = \left(\sigma_2^2 + \sigma_3^2\right) / \left(\sigma_1^2 + \sigma_2^2 + \sigma_3^2\right)$, where σ_1^2 = variance between individuals (first-level variance), σ_2^2 = variance between counties (second-level variance), and σ_3^2 = variance between cities (third-level variance). Since homogeneity within groups indicates the heterogeneity between groups, the ICC can also be used as a measure of the heterogeneity between groups. If the ICC is statistically significant, it suggests that the county- and city-level heterogeneities should not be ignored.

Third, we used a Bayesian approach for all model estimations through the R statistical package brms as an interface for the probabilistic statistical programming language Stan (Bürkner 2017). The Bayesian approach has several distinctive advantages. First, it allows for more flexibility in developing complex models. The random intercept effects can be easily implemented in the Bayesian approach. Second, it takes into account the uncertainty in estimating parameters by simulating posterior distributions. As there is only one source of zeroes in this two-stage multilevel hurdle model, the model estimation can be split into two separate parts: a multilevel MNL model for the full sample, combined with a multilevel zero-truncated NB model for only observations with positive counts. A widely applicable information criterion (WAIC), which is a fully Bayesian method for estimating out-of-sample expectations, is used to measure the Bayesian model's goodness of fit. As a generalized version of the Akaike information criterion (AIC), WAIC starts with the computed log pointwise posterior predictive density and then adds a correction for the number of valid parameters to adjust for overfitting (Vehtari et al. 2017).

Results and discussion

The results of the Bayesian multilevel MNL model and Bayesian multilevel zero-truncated NB model are presented in Table 2. The Bayesian credible interval (CI) was used to judge if a variable was significant. An effect is statistically significant at the 0.05 level if the 95% CI of the posterior mean does not include zero. We found that sociodemographics, ICT

Table 2 Empirical model results

	MNL model		Zero-truncated NB model
	Choice = Yes	Choice = Never heard of	
	Estimate (95% CI)	Estimate (95 CI%)	Estimate (95% CI)
Intercept	−3.54 (−4.40, −2.72)	−0.92 (−1.72, −0.17)	1.09 (0.53, 1.64)
Sociodemographics			
Gender			
Female	–	0.22 (0.04, 0.40)	−0.13 (−0.25, −0.02)
Male	Ref	Ref	Ref
Age	−0.05 (−0.06, −0.04)	0.03 (0.02, 0.04)	0.03 (0.00, 0.06)
Age^2	–	–	−0.0004 (−0.0007, 0)
Education level	0.18 (0.12, 0.23)	−0.28 (−0.34, −0.21)	–
Employment status			
Office worker	–	–	0.28 (0.09, 0.47)
Other worker	–	–	0.23 (0.01, 0.45)
Employer	–	−0.62 (−0.99, −0.23)	–
Student	0.50 (0.02, 1.00)	−1.67 (−2.96, −0.62)	0.51 (0.21, 0.81)
Retired	–	−0.41 (−0.69, −0.07)	–
Unemployed	Ref	Ref	Ref
Annual individual income	0.15 (0.00, 0.33)	−0.69 (−1.24, −0.25)	−0.10 (−0.20, 0.00)
Annual individual income^2	–	–	0.03 (0.00, 0.07)
Household head			
Yes	–	–	−0.14 (−0.26, −0.02)
No	Ref	Ref	Ref
ICT use			
Monthly household phone bill	–	–	−0.01 (−0.03, 0.00)
Years of using smartphones	0.05 (0.03, 0.07)	−0.06 (−0.08, −0.03)	–
Travel characteristics			
Commuting mode			
Bus	0.50 (0.25, 0.79)	–	–
Rail Transit	0.73 (0.41, 1.09)	–	–
Bike	0.64 (0.33, 0.92)	–	0.41 (0.26, 0.56)
None	Ref	Ref	Ref
Household car ownership	0.21 (0.09, 0.35)	−0.26 (−0.42, −0.11)	−0.10 (−0.17, −0.02)
Physical environment			
Living environment			
City downtown	0.91 (0.55, 1.35)	−0.98 (−1.24, −0.75)	–
City suburb	0.61 (0.19, 1.07)	−0.81 (−1.13, −0.52)	–
Large town	0.63 (0.01, 1.28)	−0.82 (−1.32, −0.38)	–
Countryside/village	Ref	Ref	Ref
House type			
Rental	–	–	0.12 (0.01, 0.22)
Self-owned/free	Ref	Ref	Ref

Table 2 (continued)

	MNL model		Zero-truncated NB model
	Choice = Yes	Choice = Never heard of	
	Estimate (95% CI)	Estimate (95 CI%)	Estimate (95% CI)
Social context			
Household members' commuting mode (Social support and modeling)			
Bike	0.37 (0.08, 0.64)	–	–
Walking	−0.22 (−0.45, −0.00)	0.23 (0.05, 0.40)	–
Social trust	0.13 (0.05, 0.23)	−0.18 (−0.27, −0.07)	–
Variance Components			
Level 2: County	0.30 (0.15, 0.52)	0.49 (0.29, 0.77)	0.03 (0.00, 0.07)
Level 3: City	2.10 (1.23, 3.35)	1.12 (0.77, 1.66)	0.02 (0.00, 0.07)
Summary statistics			
WAIC	9021		5976
ICC	0.10		0.20

use, travel characteristics, physical environment, and social context all impact participation in FBS but only sociodemographics, ICT use, travel characteristics, and physical environment impact the usage of FBS.

For the multilevel MNL model, the ICC is 0.10, meaning that 10% of the variance in the participation of FBS is attributed to the differences between counties and cities. For the multilevel zero-truncated NB model, there is 20% of the total variance in the usage of FBS is due to the differences between counties and cities. The ICC of the participation of FBS is smaller than the ICC of the usage of FBS, indicating that the quantity and quality of FBS services at county and city levels are less important in interpreting the participation of FBS. As the variances are statistically significant, the incorporation of the multilevel framework into the two-stage hurdle model is warranted.

Participation in FBS

In the multilevel MNL model, the regression coefficient denotes the expected change in the log odds of the mean per unit change in the independent variable. A positive sign for a coefficient indicates that a variable increases the odds of participating in FBS within the past week ("yes" category) or never heard of FBS ("never heard of" category) vs. not participating in FBS within the past week ("no" category), while a negative sign indicates the opposite. For the coefficients of the "yes" category, regarding the continuous variables, the odds of people participating in FBS increase with education level, annual individual income, years of using smartphones, household car ownership, and social trust and decrease with age. For the nominal variables, if employment status is student; commuting mode is bus, rail transit, or bike; living environment is city downtown, city suburb, or large town; or household members' commuting mode is bike, people are more likely to participate in FBS. If household members' commuting mode is walking, then people are less likely to participate in FBS. Since we chose the intermediate category "no" as the reference category, most coefficients of the "never heard of" category are opposite in sign but similar in magnitude to the coefficients of the "yes" category. The difference occurs in the following: gender and employment status of employer and retired become significant; for commuting modes, bus, rail transit, and bike become insignificant; for household members' commuting modes, bike becomes insignificant.

Sociodemographics

We found that gender has an insignificant effect on participation in FBS and that young people are likely to participate in FBS, which is consistent with several FBS operators' reports. Of the total Mobike users, females comprised 49% and males comprised 51% (How cycling changes cities: insights on how bikesharing supports urban development 2018); of the total Ofo users, females comprised 43% and males comprised 57% (Cycling report of major cities in China 2017 Q4 2018). The gender distribution of FBS users is more balanced than the gender distribution of SBS users. Two SBS studies conducted in China found that female SBS users comprised 38% and 28% of total users, respectively (Campbell et al. 2016; Karki and Tao 2016). The extent and underlying mechanisms of the FBS and SBS gender gap in Chinese cities merit additional research. We suspect that because FBS is flexible regarding parking and riding and offers a relatively comfortable cycling experience, FBS attracts more male users than private cycling does. Note that private cycling is gender-neutral in China as in Western countries with high levels of general cycling, e.g., the Netherlands (Pucher and Buehler 2008). In terms of age, a Mobike report suggested that the age profile of FBS users is usually younger than the average age of the general population: in Wuhan, China, 9.8% of FBS users are aged 12–20; 50.3% are aged 20–30; 24.4% are aged 30–40; 11.2% are aged 40–50; 4.3% are aged over 50 (Wuhan free-floating bike sharing trip report 2017).

Education level and annual individual income both influence participation in FBS. A higher education level increases the probability of participating in FBS; this finding is consistent with those of Li et al. (2018) and Jia and Fu (2019). With increasing annual individual income, the probabilities of participating in FBS increase. The result showing that FBS users tend to be wealthier than the general population is similar to the findings in the literature from Western countries (Chen et al. 2020b). Two reasons could explain this finding. One is that wealthier people usually have lower "time sovereignty" and FBS can serve as an extra travel option to save their travel time and thus increase their activity time. The second is that FBS operators may prefer to deploy shared bikes in wealthy areas rather than evenly distributed across the city. Because fewer people have higher incomes, although higher income individuals are more likely to use FBS, the total number of high-income FBS users is still lower than the number of FBS users in the lower-income groups, which explains why the results of Du and Cheng (2018), Xin et al. (2018), and Sun (2018) listed in the literature review section are inconsistent. Due to the small sample sizes of these studies, the differences in the survey samples largely determine their conclusions.

ICT use

The probability of participating in FBS increases with years of using smartphones. The average years of using smartphones among the respondents are only five years, which is reasonable because the mass popularity of smartphones in China was in 2011, and the survey was conducted in 2017. We believe that people with longer smartphone use histories are usually more familiar with smartphones and more inclined to embrace innovations, they are more likely to accept FBS as a new transportation mode.

Travel characteristics

People who commute by bus, rail transit, or bike are more likely to participate in FBS. The reasons can be attributed to the characteristics of the bus, rail transit, and bike modes themselves and people's travel attitude. FBS can serve as a connection mode for bus and rail transit. The bike mode includes not only ordinary bikes but also FBS. In other words, some people who chose bike as their commuting mode actually used FBS. In addition, the commuting mode choice reflects people's attitude toward the transportation mode they choose, and this attitude may influence participation in FBS. The influence of attitude has been confirmed in SBS studies (Chen et al. 2020b). People whose households own more cars are more likely to use FBS. Similar results have been found in SBS studies in Beijing, Shanghai, and Hangzhou, which revealed that SBS users have higher car ownership than nonusers do (Fishman et al. 2013).

Physical environment

Regarding the living environment, FBS is more likely to be used by and be familiar to people living in an urban environment. Because this is a national-level study, there are no elaborate built environment variables. Living in rental houses has an insignificant influence on participation in FBS.

Social context

Social support and modeling from household members significantly affect participation in FBS, with positive impacts occurring from household members who commute by bike and negative impacts occurring from household members who commute by walking. Social influence occurs at three levels: direct influence via partners and families, less direct influence via friends and colleagues, and indirect influence via the broader social and cultural context (Sherwin et al. 2014). Previous studies have revealed that people with high levels of social support and modeling (learning from those who cycle around them) are more prone to cycle (de Geus et al. 2007; Sherwin et al. 2014). Titze et al. (2008) suggested that if individuals have family or friends who cycle, then they engage in cycling more often. This study confirms that social support and modeling also hold for participation in FBS. Furthermore, individuals may not only learn from those who cycle but also learn from those who walk. Household members who commute by bike are more accepting of FBS and thus positively affect the respondents' participation in FBS. However, walking and FBS are largely competitive because people who walk to work are likely to live in densely populated areas where they may not need to use a bike, or because the parking of shared bikes invades walking space and blocks pedestrians. Household members who commute by walking are less accepting of FBS and thus negatively affect the respondents' participation in FBS. Social trust is positively related to participation in FBS. Since FBS involves using a fleet of bikes with other strangers, those who find it difficult to trust strangers, or who more generally fear the unknown, may be more reluctant to participate.

Usage of FBS

In the multilevel zero-truncated NB model, the regression coefficient denotes the expected change in the log of the mean per unit change in the independent variable. The signs of coefficients reflect the direction in which each variable influences the usage of FBS. For the continuous variables, the usage of FBS increases with age, and the quadratic term of annual individual income and decreases with the quadratic term of age, annual individual income, monthly household phone bill, and household car ownership. For the nominal variables, if the gender is male, the employment status is office worker, other worker, or student, the commuting mode is bike, the individual is not the household head, then people are more likely to make more FBS trips.

Sociodemographics

We found that males and middle-aged people are likely to make more FBS trips. A Mobike report also confirms that male users take more trips than female users (The Mobike white paper: bike-share in the city 2017). Figure 2 shows the marginal effect of age, i.e., the predicted usage of FBS generated by the model when varying the age variable and holding other variables at their mean values. For models with quadratic terms, the visualization of marginal effects makes the association between the focal variable and the outcome more intuitive and easier to understand. As the original and quadratic terms of age are both significant and have opposite signs, the usage of FBS is higher for middle-aged people (around the mean age of 39 years old) and lower for people who are younger or older. Research relating to the use frequency of different age groups is limited. Chen et al. (2020a) found that age was not significant when analyzing factors influencing the use frequency of FBS. However, their sample size was rather small (169 completed questionnaires).

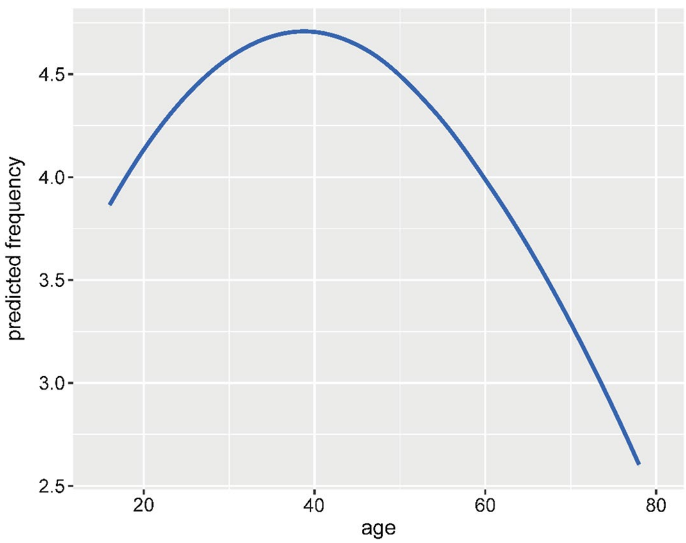

Fig. 2 Marginal effect of age

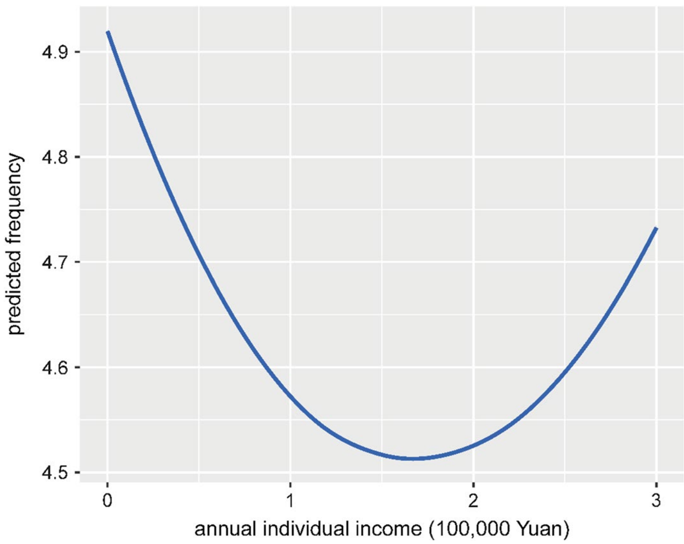

Fig. 3 Marginal effect of annual individual income

Annual individual income influences the usage of FBS in a nonlinear way since its original and quadratic terms are both significant and have opposite signs. Figure 3 shows the marginal effect of annual individual income. The usage of FBS decreases to the annual individual income of 170,000 Yuan and then increases. The average annual individual income of the sample is 50,000 Yuan. High-income FBS users (3.4 times the average income) have the lowest usage of FBS, followed by the highest-income and upper-middle-income users, and low-income users have the highest usage of FBS. The literature has often focused on the effect of income on participation in FBS, without establishing whether income influences the usage of FBS. Education level does not affect individuals' usage of FBS, which is consistent with Chen et al.'s study (2020a).

The household head variable decreases the usage of FBS. As the main economic source, the household head uses cars more and uses public transit, walking, and cycling less than other household members, especially in the Chinese context, where most households own no more than one car (Yang et al. 2017).

ICT use

The monthly household phone bill variable decreases the usage of FBS. The monthly household phone bill includes the cost of mobile phones, TV, and internet for the entire household. Since there are many communication providers in China offering a variety of packages, we believe that people familiar with ICT are more likely to find cheaper packages and their usage of FBS is likely to be higher. The impact of ICT use on the usage of FBS was confirmed by Chen et al. (2020a), who found that people with the largest data packages were more likely to be frequent users.

Travel characteristics

For people who participate in FBS, commuting by bike increases the usage of FBS. Since the bike mode includes not only ordinary bikes but also FBS, and the commuting mode choice reflects people's attitude toward the bike mode, this conclusion is reasonable. The household car ownership variable has opposite effects on participation in FBS and the usage of FBS. Once the decision to participate in FBS has been made, the usage of FBS is lower for those with household car ownership. Chen et al. (2020a) also suggested that the frequent users of FBS are in the noncar group.

Physical environment

The usage of FBS is higher for people living in rental houses. Intuitively, a rental house is near an individual's office, convenient for public transportation, and has limited parking space (Zhang et al. 2018), individuals should be more likely to use FBS. Although no previous studies have investigated the influence of rental housing on FBS use, FBS has become a valuable amenity for renters. A study in Beijing shows that every one-point increase in the accessibility to FBS generates a housing rental premium worth 28 Yuan (Qiao et al. 2021).

Sensitivity analysis

We conducted a sensitivity analysis to ensure the robustness of the results. Because the names of cities and counties were hidden in CHFS data, we cannot explicitly exclude people who lived in cities or counties without FBS services. This is one of the important reasons why we used the multilevel models to capture the homogeneity of cities and counties, and the most important source of homogeneity is the quantity and quality of FBS services. However, we found that no one chose the "yes" category in 92 cities out of a total of 161, which could be due to two reasons: either the city did not have FBS service, or the survey in the city did not cover people who used FBS during the reference period. Since we could not distinguish between these two possibilities, we excluded the entire sample of the 92 cities where FBS services probably did not exist and re-estimated the Bayesian multilevel MNL model to check the robustness of the results. The remaining data contained 4316 people in 79 cities where FBS services definitely existed. The results of the new model are shown in Table 3. Except that gender and employment status of student became insignificant in the "no" category vs. the "never heard of" category, the coefficients of the new model changed only slightly in magnitude compared to the coefficients of the original model, which confirmed the robustness of the results. The reason for the insignificant employment status of student was that there was no sample of students in the "never heard of" category in the new dataset.

Conclusions

In this study, we developed a conceptual framework of the determinants of FBS use and characterized the factors influencing participation in and the usage of FBS. In terms of social context, we found that household members who commute by bike have a positive effect on individuals' participation in FBS, while household members who commute by

Table 3 Empirical model results for sensitivity analysis

	MNL model	
	Choice = Yes	Choice = Never heard of
	Estimate (95% CI)	Estimate (95 CI%)
Intercept	−3.50 (−4.39, −2.44)	−0.58 (−1.49, 0.29)
Sociodemographics		
Age	−0.05 (−0.06, −0.04)	0.03 (0.02, 0.04)
Education level	0.18 (0.11, 0.26)	−0.35 (−0.43, −0.26)
Employment status		
Employer	–	−0.71 (−1.19, −0.21)
Student	0.73 (0.11, 1.43)	–
Retired	–	−0.37 (−0.71, −0.05)
Unemployed	Ref	Ref
Annual individual income	0.14 (0.00, 0.31)	−0.34 (−0.67, −0.01)
ICT use		
Years of using smartphones	0.04 (0.01, 0.08)	−0.04 (−0.07, −0.01)
Travel characteristics		
Commuting mode		
Bus	0.57 (0.24, 0.87)	–
Rail Transit	0.73 (0.41, 1.09)	–
Bike	0.28 (0.00, 0.52)	–
Household car ownership	0.22 (0.03, 0.38)	−0.40 (−0.63, −0.16)
Physical environment		
Living environment		
City downtown	1.40 (0.77, 2.04)	−1.23 (−1.56, −0.89)
City suburb	1.00 (0.36, 1.68)	−0.98 (−1.40, −0.49)
Large town	1.28 (0.26, 2.17)	−0.87 (−1.42, −0.21)
Countryside/village	Ref	Ref
Social context		
Household members' commuting mode (Social support and modeling)		
Bike	0.20 (0.02, 0,40)	–
Walking	−0.22 (−0.45, −0.00)	0.33 (0.07, 0.59)
Social trust	0.13 (0.00, 0.26)	−0.19 (−0.31, −0.05)
Variance Components		
Level 2: County	0.22 (0.06, 0.50)	0.35 (0.12, 0.72)
Level 3: City	1.85 (1.00, 3.42)	1.10 (0.66, 1.80)
Summary statistics		
WAIC	4906	
ICC	0.12	

walking have a negative effect. Social trust is positively related to participation in FBS. In terms of ICT use, years of using smartphones have a positive effect on individuals' participation in FBS, and monthly household phone bill has a negative effect on individuals' usage of FBS. In terms of sociodemographics, age and individual income have nonlinear effects on the usage of FBS. Methodologically, we distinguished between the decision to participate in FBS and the corresponding usage of FBS by using a two-stage multilevel hurdle model. The results confirm the hypothesis that considering a model explaining only participation in FBS or the usage of FBS would bias the impact of factors. In addition, as the dataset for this study covers 29 provinces and municipalities of China, the results are not city-specific but universal.

There are also some practical implications. The findings of our study highlight the necessity of promoting FBS use according to physical environments and social context. As the model also shows the existence of exclusive variables that only affect participation in or the usage of FBS, policymakers and FBS operators should use specific instruments if they want to expand FBS users or increase the usage of FBS. A supportive physical environment and social context is a potential determinant of participation in FBS and should be considered when designing interventions. The finding that frequent users were more likely to come from households living in rental houses suggests the potential for expansion of FBS to neighborhoods with more tenants. The FBS operators could join forces with communities to use social media to propagate FBS programs to expand the FBS user base since the influences of social support and modeling and social trust on participation in FBS has been revealed. The impact of FBS propagation may increase over time as people see more of their household members and neighbors using FBS. The idea of using FBS can diffuse through the population and can develop new social norms. The government is suggested to promote the integration of FBS and public transit operators because individuals who commute by public transit are more likely to participate in FBS. Our study found that social context had a limited impact on increasing the usage of FBS by existing users, while the physical environment had a more important impact. The government could take action to provide a supportive environment for cycling, especially in cities with insufficient bike lanes and limited parking spaces. In addition, the FBS operators could offer more promotions to attract existing users to use FBS more often. Promotions could include not only reduced usage prices for regular users but also additional incentives such as monetary rewards for users who cycle from the oversupplied area to the undersupplied area.

This study has several limitations. First, the respondents in each household were the people with the most knowledge of the family's economic situation, which means that respondents were more likely to be those with higher education, higher income, or older age in the household, and they may have been overrepresented in this study. Second, social support and modeling could take the form of direct influence from the family, less direct influence from friends and peers, and indirect influence from the social and cultural context (Sherwin et al. 2014). Only the direct social influence was investigated in this study. Social trust refers to trust in strangers in general in this study, and it would be more straightforward to specify the social trust variable as trust in the FBS system or in the strangers using FBS (e.g., trust that they will take good care of the bikes to ensure good service quality). Third, although we used a multilevel framework to capture the county- and city-level variations of FBS use, due to data limitation, the direct influence of quantity and quality of FBS services at county and city levels on FBS use is unclear. Future research should explicitly consider these factors.

Author contributions The authors confirm contribution to the paper as follows: conceptualization, data curation, formal analysis, funding acquisition, methodology, and writing—original draft: YD; methodology and writing—review & editing: PZ. Both authors reviewed the results and approved the final version of the manuscript.

Funding This work was supported by the Zhejiang Provincial Philosophy and Social Science Planning Project [Grant numbers 19NDQN351YB], and the National Natural Science Foundation of China [grant numbers 51978617].

Data availability The original dataset is available for public download and use upon request from China Household Finance Survey website https://chfs.swufe.edu.cn/, administered by the Survey and Research Center for China Household Finance of the Southwestern University of Finance and Economics.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Code availability The custom code is available from authors upon request.

References

Bürkner, P.: Brms: an R package for bayesian multilevel models using stan. J. Stat. Softw. (2017). https://doi.org/10.18637/jss.v080.i01

Cameron, A.C., Trivedi, P.K.: Regression-based tests for overdispersion in the Poisson model. J. Econom. **46**(3), 347–364 (1990). https://doi.org/10.1016/0304-4076(90)90014-K

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

Chen, M., Wang, D., Sun, Y., Waygood, E.O.D., Yang, W.: A comparison of users' characteristics between station-based bikesharing system and free-floating bikesharing system: case study in Hangzhou, China. Transportation **47**(2), 689–704 (2020a). https://doi.org/10.1007/s11116-018-9910-7

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

Cycling report of major cities in China 2017 Q4. Ofo, China Academy of Transportation Science. https://www.sohu.com/a/216562254_99949100 (2018) Accessed 20 Feb 2021

de Geus, B., De Bourdeaudhuij, I., Jannes, C., Meeusen, R.: Psychosocial and environmental factors associated with cycling for transport among a working population. Health Educ. Res. **23**(4), 697–708 (2007). https://doi.org/10.1093/her/cym055

DeMaio, P.: Bike-sharing: history impacts, models of provision, and future. J. Public Transp. **12**(4), 41–56 (2009). https://doi.org/10.5038/2375-0901.12.4.3

Du, M., Cheng, L.: Better understanding the characteristics and influential factors of different travel patterns in free-floating bike sharing: evidence from Nanjing, China. Sustainability **10**(4), 1244 (2018). https://doi.org/10.3390/su10041244

Du, Y., Deng, F., Liao, F.: A model framework for discovering the spatio-temporal usage patterns of public free-floating bike-sharing system. Transp. Res. Part C Emerg. Technol. **103**, 39–55 (2019). https://doi.org/10.1016/j.trc.2019.04.006

Fishman, E.: Bikeshare: a review of recent literature. Transp. Rev. **36**(1), 92–113 (2016). https://doi.org/10.1080/01441647.2015.1033036

Fishman, E., Washington, S., Haworth, N.: Bike share: a synthesis of the literature. Transp. Rev. **33**(2), 148–165 (2013)

Gan, L., Yin, Z., Jia, N., Xu, S., Ma, S., Zheng, L.: Data you need to know about China. Springer, Heidelberg (2014)

Gu, T., Kim, I., Currie, G.: To be or not to be dockless: empirical analysis of dockless bikeshare development in China. Transp. Res. Part A Policy Pract. **119**, 122–147 (2019). https://doi.org/10.1016/j.tra.2018.11.007

Guidon, S., Becker, H., Dediu, H., Axhausen, K.W.: Electric bicycle-sharing: a new competitor in the urban transportation market? An empirical analysis of transaction data. Transp. Res. Rec. J. Transp. Res. Board. **2673**(4), 15–26 (2019). https://doi.org/10.1177/0361198119836762

Guidon, S., Reck, D.J., Axhausen, K.: Expanding a(n) (electric) bicycle-sharing system to a new city: prediction of demand with spatial regression and random forests. J. Transp. Geogr. **84**, 102692 (2020). https://doi.org/10.1016/j.jtrangeo.2020.102692

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

Heinen, E., Maat, K., Wee, B.V.: The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. Transp. Res. Part D Transp. Environ. **16**(2), 102–109 (2011). https://doi.org/10.1016/j.trd.2010.08.010

Hirsch, J.A., Stratton-Rayner, J., Winters, M., Stehlin, J., Hosford, K., Mooney, S.J.: Roadmap for free-floating bikeshare research and practice in North America. Transp. Rev. **39**(6), 706–732 (2019). https://doi.org/10.1080/01441647.2019.1649318

How cycling changes cities: insights on how bikesharing supports urban development. World Resources Institute, Mobike Global. https://mobike.com/global/blog/post/cycling-changes-cities (2018) Accessed 20 Feb 2021

Jia, Y., Fu, H.: Association between innovative dockless bicycle sharing programs and adopting cycling in commuting and non-commuting trips. Transp. Res. Part A Policy Pract. **121**, 12–21 (2019). https://doi.org/10.1016/j.tra.2018.12.025

Karki, T.K., Tao, L.: How accessible and convenient are the public bicycle sharing programs in China? Experiences from Suzhou City. Habitat Int. **53**, 188–194 (2016). https://doi.org/10.1016/j.habitatint.2015.11.007

Li, A., Zhao, P., Huang, Y., Gao, K., Axhausen, K.W.: An empirical analysis of dockless bike-sharing utilization and its explanatory factors: case study from Shanghai, China. J. Transp. Geogr. **88**, 102828 (2020). https://doi.org/10.1016/j.jtrangeo.2020.102828

Li, X., Zhang, Y., Sun, L., Liu, Q.: Free-floating bike sharing in Jiangsu: users' behaviors and influencing factors. Energies **11**(7), 1664 (2018). https://doi.org/10.3390/en11071664

Link, C., Strasser, C., Hinterreiter, M.: Free-floating bikesharing in Vienna – a user behaviour analysis. Transp. Res. Part A Policy Pract. **135**, 168–182 (2020). https://doi.org/10.1016/j.tra.2020.02.020

Mullahy, J.: Specification and testing of some modified count data models. J. Econom. **33**(3), 341–365 (1986)

Nolan, J.M., Schultz, P.W., Cialdini, R.B., Goldstein, N.J., Griskevicius, V.: Normative social influence is underdetected. Pers. Soc. Psychol. Bull. **34**(7), 913–923 (2008). https://doi.org/10.1177/0146167208316691

Nyhan, R.C.: Changing the paradigm: trust and its role in public sector organizations. Am. Rev. Publ. Administ. **30**(1), 87–109 (2000). https://doi.org/10.1177/02750740022064560

Pucher, J., Buehler, R.: Making cycling irresistible: lessons from the Netherlands Denmark and Germany. Transp. Rev. **28**(4), 495–528 (2008)

Qiao, S., Gar-On Yeh, A., Zhang, M.: Capitalisation of accessibility to dockless bike sharing in housing rentals: evidence from Beijing. Transp. Res. Part D Transp. Environ. **90**, 102640 (2021). https://doi.org/10.1016/j.trd.2020.102640

Shen, Y., Zhang, X., Zhao, J.: Understanding the usage of dockless bike sharing in Singapore. Int. J. Sustain. Transp. **12**(9), 686–700 (2018). https://doi.org/10.1080/15568318.2018.1429696

Sherwin, H., Chatterjee, K., Jain, J.: An exploration of the importance of social influence in the decision to start bicycling in England. Transp. Res. Part A Policy Pract. **68**, 32–45 (2014). https://doi.org/10.1016/j.tra.2014.05.001

Sun, Y.: Sharing and riding: how the dockless bike sharing scheme in China shapes the city. Urban Sci. **2**(3), 68 (2018). https://doi.org/10.3390/urbansci2030068

Teixeira, J.F., Silva, C., Moura E Sá, F.: Empirical evidence on the impacts of bikesharing: a literature review. Transp. Rev. **41**(3), 329–351 (2021). https://doi.org/10.1080/01441647.2020.1841328

The Mobike white paper: bike-share in the city. Mobike Global, Beijing Tsinghua Tongheng Planning and Design Institute, China New Urbanization Research Institute. https://mobike.com/sg/blog/post/mobikewhitepaper (2017) Accessed 20 Feb 2021

Titze, S., Stronegger, W.J., Janschitz, S., Oja, P.: Association of built-environment, social-environment and personal factors with bicycling as a mode of transportation among Austrian city dwellers. Prev. Med. **47**(3), 252–259 (2008). https://doi.org/10.1016/j.ypmed.2008.02.019

Tu, Y., Chen, P., Gao, X., Yang, J., Chen, X.: How to make dockless bikeshare good for cities: curbing oversupplied bikes. Transp. Res. Rec. J. Transp. Res. Board. **2673**(6), 618–627 (2019). https://doi.org/10.1177/0361198119837963

Van, H.T., Choocharukul, K., Fujii, S.: The effect of attitudes toward cars and public transportation on behavioral intention in commuting mode choice—a comparison across six Asian countries. Transp. Res. Part A Policy Pract. **69**, 36–44 (2014). https://doi.org/10.1016/j.tra.2014.08.008

Vehtari, A., Gelman, A., Gabry, J.: Practical bayesian model evaluation using leave-one-out cross-validation and WAIC. Stat. Comput. **27**(5), 1413–1432 (2017). https://doi.org/10.1007/s11222-016-9696-4

Wuhan free-floating bike sharing trip report. Wuhan transportation development strategy Institute. http://www.199it.com/archives/630387.html (2017) Accessed 20 Feb. 2021

Xin, F., Chen, Y., Wang, X., Chen, X.: Cyclist satisfaction evaluation model for free-floating bike-sharing system: a case study of Shanghai. Transp. Res. Rec. J. Transp. Res. Board. **2672**(31), 21–32 (2018). https://doi.org/10.1177/0361198118770193

Xing, Y., Handy, S.L., Mokhtarian, P.L.: Factors associated with proportions and miles of bicycling for transportation and recreation in six small US cities. Transp. Res. Part D Transp. Environ. **15**(2), 73–81 (2010). https://doi.org/10.1016/j.trd.2009.09.004

Yang, S., Fan, Y., Deng, W., Cheng, L.: Do built environment effects on travel behavior differ between household members? A case study of Nanjing, China. Transp. Policy. **60**, 1–17 (2017). https://doi.org/10.1016/j.tranpol.2017.12.006

Zhang, M., He, S., Zhao, P.: Revisiting inequalities in the commuting burden: institutional constraints and job-housing relationships in Beijing. J. Transp. Geogr. **71**, 58–71 (2018). https://doi.org/10.1016/j.jtrangeo.2018.06.024

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Yiling Deng is an Associate Professor at the School of Design and Architecture at Zhejiang University of Technology, China and serves as the deputy director of the Department of Urban Planning at Zhejiang University of Technology. He holds a PhD from Southeast University, China. His research interests include travel behavior analysis, transportation modeling, and sustainable transportation.

Pengjun Zhao is a Professor in Urban and Regional Planning in the School of Urban and Environmental Sciences at Peking University, and the director of School of Urban Planning and Design of Peking University Shenzhen Graduate School. He is also the Editor-in-Chief for Cities (Elsevier). He obtained his PhD degree and postdoctoral training in Urban Planning at University of Groningen, the Netherlands. His research mostly focuses on sustainable transportation, travel demand management, sustainable mobility and transport equality.