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Exploring Influential Factors of Free-Floating Bike-Sharing Usage Frequency before and after COVID-19

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Abstract: In order to better understand the impact of COVID-19 on the free-floating bike-sharing (FFBS) system and the potential role of FFBS played in the pandemic period, this study explores the impact mechanism of travel frequency of FFBS users before and after the pandemic. Using the online questionnaire collected in Nanjing, China, we first analyze the changes of travel frequency, travel distance, and travel duration in these two periods. Then, two ordered logit models are applied to explore the contributing factors of the weekly trip frequency of FFBS users before and after COVID-19. The results show that: (1) While the overall travel duration and travel distance of FFBS users decreased after the pandemic, the trip frequency of FFBS users increased as the travel duration increased. (2) Since COVID-19, attitude perception variables of the comfort level and the low travel price have had significantly positive impacts on the weekly trip frequency of FFBS users. (3) Respondents who use FFBS as a substitution for public transport are more likely to travel frequently in a week after the outbreak of COVID-19. (4) The travel time in off-peak hours of working days, weekends, and holidays has a significantly positive correlation with the trip frequency of FFBS users. Finally, several relevant policy recommendations and management strategies are proposed for the operation and development of FFBS during the similar disruptive public health crisis.

Keywords: free-floating bike sharing; COVID-19; travel frequency; influential factors; ordered logit models

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1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic has spread globally since its emergence at the end of 2019, resulting in numerous infections and deaths. Its effects have been felt across all aspects of daily life, such as telecommuting, online shopping [1], grocery [2], healthcare [3,4] and recreation [5]. For the transportation department, the pandemic has profoundly impacted travel patterns. Existing studies have shown that due to the high possibility of the spread of coronavirus in confined spaces [6,7], public transport ridership has dropped dramatically. A modal shift from public transport to individual cars and the ride-hailing service whose operation relies on private cars was noticed [8,9], as individual car travel is regarded as a safer and more reliable mode [10]. However, such a modal shift trend will lead to a series of environmental problems. Given these concerns, active travel, a travel mode which can reduce carbon emissions, traffic congestion, and environmental pollution, can be considered as an alternative to public transport and private cars. Moreover, this travel mode provides the possibility of retaining the resilience of the entire transport system during the pandemic when public transport is regarded as an unreliable travel mode [11].

As an important option of active travel, a bike sharing system (BSS) provides convenience for the short-distance travel and the connection to public transport, with many advantages such as convenience, environmental benefits, and positive health effects [12]. The existing BSS can be divided into two categories: public bike sharing (PBS, i.e., docked bike sharing) and free-floating bike sharing (FFBS, i.e., dockless bike sharing) [10]. PBS is invested in and managed by the government and is operated as a station-to-station system; users need to rent a bike at a station and return it to another [13]. FFBS is operated by enterprises and distributed in predefined operational areas, users could rent and return it anywhere at users' convenience [14]. During the pandemic, the role of BSS in urban transportation systems changed significantly. For instance, the usage of PBS increased during lockdowns and showed a higher increase rate after the lockdown ease in London, UK, while the morning peak trips and short duration trips maintained a lower usage level [1]. In the US city of Columbus, Ohio, the lockdown resulted in substantial PBS substitutive trips for public transport [15]. In Lisbon, Portugal, the proportion of public transport trips (21.9%) during lockdowns was surpassed by PBS (27.3%) [10], and the cycling trips for entertainment or exercise increased, while the number of commuting trips decreased [16]. In addition, there are distinct differences in factors affecting urban residents' choice of BSS travel before and after the pandemic. Before the pandemic, the most influential motivations of using PBS were mainly the service quality and perceived environmental and health benefits, while the motivations associated with avoiding public transport and maintaining social distancing became more important after the pandemic [17]. Although several existing studies have focused on the change and influential factors of PBS ridership during the COVID-19 period, less attention has been given to the contrast of influential factors of FFBS trips before and after COVID-19. In view of this, this study examines the contributing factors of the weekly trip frequency of FFBS users during these two periods. The results could provide a deeper understanding of the impact of COVID-19 on FFBS systems for policymakers and urban planners, and support for operational management of such disruptive public health crisis at the theoretical level.

The contributions of this study are mainly concentrated on two aspects: (1) Based on the questionnaire survey of the travel behavior of FFBS users in Nanjing, China, the changes of the travel frequency, travel distance, and travel time of FFBS users before and after the COVID-19 are compared. (2) Considering variables such as individual attributes, travel attributes, and attitude perception, two ordered logit models are established to compare and analyze the influential factors of FFBS users' trip frequency before and after the pandemic. Furthermore, several countermeasures and suggestions are provided for the operation and development of FFBS during the pandemic.

2. Literature Review

2.1. Impact of COVID-19 Pandemic on BSS

This study mainly reviews the literature from two aspects: the macro-system perspective (based on the analysis of BSS operation data) and the micro-user perspective (based on the travel behavior survey or the stated preference survey).

2.1.1. Macro-System Perspective

Existing studies based on the travel data provided by operators or officials mainly compared and analyzed the ridership of BSS before and after the pandemic, predicted the ridership in the future, and investigated the physical space factors of the BSS travel.

Kim and Lee [18] examined the effect of COVID-19 on the PBS ridership and various determining factors of PBS usage, using an origin–destination analysis and spatial regression models with public bike ridership data from a Seoul open dataset. The results confirmed that the variables of public parks and the accessibility to subway stations significantly influenced the increase of PBS ridership since the COVID-19 outbreak. Using CoGo PBS trip data together with Automatic Passenger Counter (APC) data from the Central Ohio Transit Authority (COTA), Kwon and Akar [15] identified PBS trips and public transit ridership patterns during COVID-19 and classified bike-share as a substitutive and complementary mode to public transit. Then, they established binary logit models to analyze the determinants of substitutive trips. The results showed that the COVID-19 pandemic led to a decrease in bus passengers and an increase in PBS trips, and PBS might compete with public transport in short trips. Zhang and Li [19] evaluated the impacts of both the introduction of the first bike lane and the COVID-19 pandemic on the change of travel mode in Beijing, using the proposed comprehensive selection and potential variable model. The research results showed that the COVID-19 pandemic significantly inhibited the shift to FFBS for either long or short trips of high-carbon groups, and significantly encouraged the low-carbon community to choose FFBS for short trips. Arias-Molinares et al. [20] used the GPS data provided by three different micro-mobile operators in Madrid to compare the differences in spatio-temporal travel patterns before and after the pandemic. The results revealed that the COVID-19 pandemic led to about 10% reduction in micro-mobile travel, which was relatively low compared with the 80% ridership reduction of public transport systems. By multiple regression analysis, the results also showed that residential and commercial areas became increasingly important after the pandemic, while the workplace, education, and transportation facilities lost relevance to remote working and online learning. Using the travel data of Citibike in New York City, Bi et al. [21] compared and analyzed the spatio-temporal flow pattern of PBS and the connectivity of the network before and after the pandemic. A multivariate survey results of users and travel characteristics showed that ridership of PBS fell severely during the pandemic, but quickly recovered to pre-pandemic levels within a few months. Ridership of PBS increased in areas near supermarkets, parks, and hospitals, and there were significant differences of gender, age, and cycling patterns in response to potential risks. Based on the travel data of public bicycles and shared bicycles in Nanjing, China, Hua et al. [22] discussed the usage pattern of PBS during the pandemic from the perspectives of stations, users, and bicycles. From the perspective of users, PBS became more important during the COVID-19 pandemic, and middle-aged and elderly people were more dependent on this service. The network connectivity and peak phenomena of PBS decreased during the pandemic. Using smart card data from PBS collected in Nanjing, China, Chen et al. [23] concluded that the COVID-19 pandemic accelerated the decline of the proportion of female and young commuters, and the users of commuting and transfer increased. Buchel et al. [24] analyzed the bicycle traffic situation in Basel and Zurich before, during, and after the lockdown, and established a random forest regression model to predict the total bicycle travel volume, and the results showed that the bicycle traffic volume had a short-term decline and quickly recovered to the level before the lockdown. Berezvai [25] used the panel regression method to study the impact of COVID-19 on the passenger flow of PBS, and the results showed that the government's strict measures had a significant and positive impact on the use of PBS, especially in residential areas and areas close to parks. However, ridership of PBS declined after the first wave of the pandemic passed and restrictions were lifted. Shang et al. [26] researched the impact of COVID-19 on user behavior and the environmental benefits of PBS using big data technology, and the results showed that the pandemic increased the average travel time of PBS users. Wang and Noland [27] analyzed the data of Citi bicycle and subway ridership in New York, and through data visualization and time series modeling, the results showed that the amount of subway ridership and PBS usage declined substantially in the early stages of the pandemic; after then, PBS usage was almost back to normal, while subway ridership was still far below that before COVID-19.

2.1.2. Micro-User Perspective

Several studies analyzed the travel demand and use motivation of BSS users during the pandemic period from the perspective of users using a questionnaire survey.

Through 16 semi-structured interviews, Teixeira et al. [11] discussed users' views on Lisbon's PBS system during the pandemic. The results showed that the PBS provided users with a mode of transportation with a low risk of infection, and ensured their travel needs in destructive events. Bergantino et al. [28] conducted a nationwide online survey in Italy to study the influential factors of potential users' PBS usage during the pandemic. Through factor analysis, ordered logit, and probit regression methods, the results showed that the main influential factors were convenient cycling environment, infrastructure, cycling safety, and intelligent and convenient services. Jobe and Griffin [29] distributed online surveys regarding the use of PBS systems during the pandemic in several major cities in the United States, and the results showed that unemployed people and medium-frequency riders were more likely to increase the use of PBS during the pandemic. Teixeira et al. [10] conducted a travel behavior survey in Lisbon, compared and analyzed users' travel attributes, changes in travel modes, and safety attitude motivation related to the pandemic before and after the pandemic, and the results showed that the perceived safety of PBS had a small decline.

2.2. Research Gap

Existing studies have analyzed the impact of COVID-19 on the BSS from the macro-level based on operational data and examined the influential factors of BSS trips during the pandemic. However, few studies have focused on the differences in influential factors of bike-sharing users' trips frequency before and after the pandemic. Moreover, these studies mainly focused on PBS; the research on FFBS is insufficient. In view of this, this study focuses on FFBS, compares and analyzes the influential factors of the weekly trip frequency of FFBS users before and after the pandemic. The results may provide a better understanding of the characteristics of FFBS users before and during the pandemic and support for their operation and management theoretically when similar large-scale safety incidents occur.

3. Data

3.1. Survey Area

Nanjing, the capital city of Jiangsu Province, is an important comprehensive transportation hub and an important central city in eastern China [30–32]. Nanjing has three bike-sharing companies, MoBike, DidiBike, and HalloBike, with a total of 350,600 free-floating bikes in operation [22]. As illustrated in Figure 1, the main urban area of Nanjing is divided into two sub-areas [33]: the urban center area (including Xuanwu District, Qinhuai District, Gulou District, and Jianye District) and the suburban districts (including Qixia District, Yuhuatai District, Pukou District, Jiangning District, Liuhe District, Lishui District, and Gaochun District).

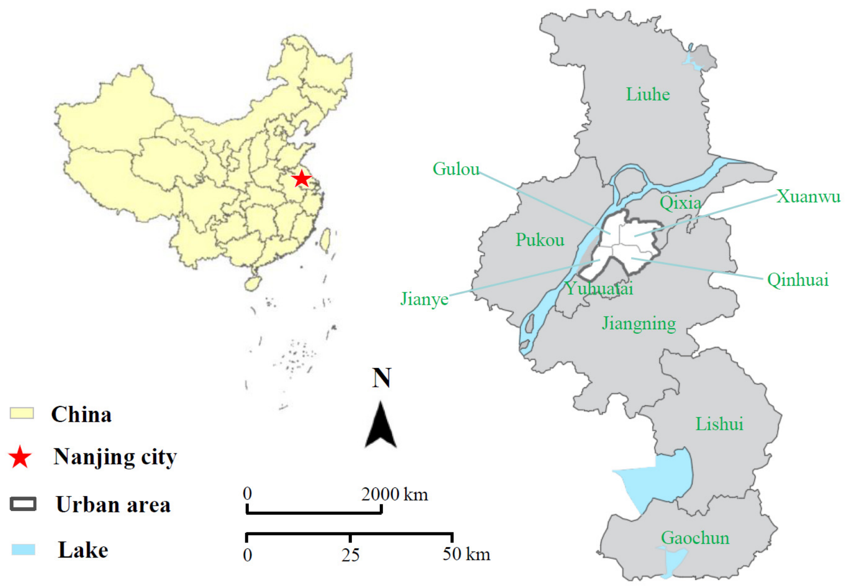

Figure 1. Location and regional division of Nanjing city.

3.2. Data Source and Survey Design

Data collection was conducted from 12 February to 26 February, 2022 in Nanjing, China. Considering the risk of infection and the need for safe social distancing during the pandemic, the questionnaire was designed using the platform www.wjx.cn/ (accessed on 7 February 2022) and the data were collected through online channels such as WeChat and QQ. The IP address was restricted to Nanjing and each IP address could fill in the questionnaire only once. To encourage participants to join the survey, we set cash rewards for them after they filled out the questionnaire.

The objective of this study was to explore the factors influencing the weekly trip frequency of FFBS users before and after the pandemic. The questionnaire included three parts: (1) Attitudes toward FFBS trips before and after the pandemic, including easy to park and pick up, low travel cost, convenient payment, high security, and high amenity. (2) Travel attributes before and after the pandemic: whether FFBS substitutes for other travel modes (i.e., walking, biking, bus, subway, private automobile, taxi), travel duration, travel distance, travel purpose (i.e., commuting, non-commuting), and travel time. (3) Basic attributes, including gender, age, occupation, education level, and income level.

Since we aimed to examine the influential factors of FFBS usage frequency, the users of FFBS were the target population in this study. Before starting the questionnaire, whether the respondents were FFBS users was confirmed first. Then, respondents were informed that the pre-pandemic period (before COVID-19) refers to the time before December 2019, while the post-pandemic period (after COVID-19) refers to that from December 2019 to the current time when participants in the survey received the questionnaire.

The survey mainly included three parts. In the first part, the attitudes and perceptions of FFBS users before and after the pandemic were captured, using a five-point Likert scale from “strongly disagree” to “strongly agree” [34]. In the second part, respondents were asked about their travel attributes before and after the pandemic in the two periods separately. Lastly, the survey collected sociodemographic characteristics of the respondents. A total of 150 respondents were investigated, 127 valid samples were collected after cleaning the samples with missing data (e.g., some participants were unwilling to provide private information such as income and age), and the recovery rate was 84.67%.

3.3. Respondent Attributes

The demographic information of investigated FFBS users is shown in Table 1. In terms of gender, the proportion of males (55.12%) was slightly higher than that of females (44.88%), which is consistent with the results of previous studies [35]. The majority of respondents were aged between 19 and 40. In terms of occupation, students, government officers, and enterprise workers account for a large proportion of FFBS users, which is in accordance with the result of Li et al. [36]. As for the education level of the respondents, many participants were undergraduates, which is in line with the research results that the people with higher education have a positive promoting effect on the use of shared bikes [37]. The distribution of each income level is relatively average, among which the middle-income group accounts for a comparatively high proportion, while the high-income group accounts for the lowest proportion, which is consistent with the result of Du and Cheng [38].

Table 1. Demographic information of the sample.

		Respondents (N = 127)	Percentage (%)
Gender	Male	70	55.12
	Female	57	44.88
Age	≤18	2	1.57
	19–40	111	87.40
	41–65	14	11.02

Table 1. *Cont.*

		Respondents (N = 127)	Percentage (%)
Level of education	Middle school or below	7	5.51
	Senior high school	18	14.17
	Undergraduate school	93	73.23
	Graduate school or above	9	7.09
Occupation	Students	37	29.13
	Government officer	15	11.81
	Enterprise employee	45	35.43
	Teachers	5	3.94
	Retiree	1	0.79
	Others	24	18.90
Income level (CNY/month)	≤3000	35	27.56
	3001–6000	38	29.92
	6001–10,000	37	29.13
	>10,000	17	13.39

4. Characteristic Analysis

4.1. Weekly Travel Freqeuncy of FFBS Users before and after COVID-19

Figure 2 compares the proportion of users' travel frequency by FFBS in a week before and after pandemic. The majority of respondents indicated that they had a travel frequency of less than or equal to 3 in a week (69.3% before COVID-19 and 80.3% after COVID-19), suggesting that most of those participants are low-frequency FFBS users. The proportion of high-frequency users (weekly trip frequency ≥ 5) decreased slightly after the pandemic, which is consistent with the study by Teixeira et al. [10]. After the pandemic's emergence, the number of people whose travel frequency is less than or equal to one increased the most (from 30.7% to 41.7%). The reason for reducing or quitting the use of FFBS may be related to the worries about the infection risk of shared bikes; another possible reason is that the total number of commuting and leisure trips decreased due to telecommuting, online meetings, and online shopping, which are becoming more common during the pandemic [11].

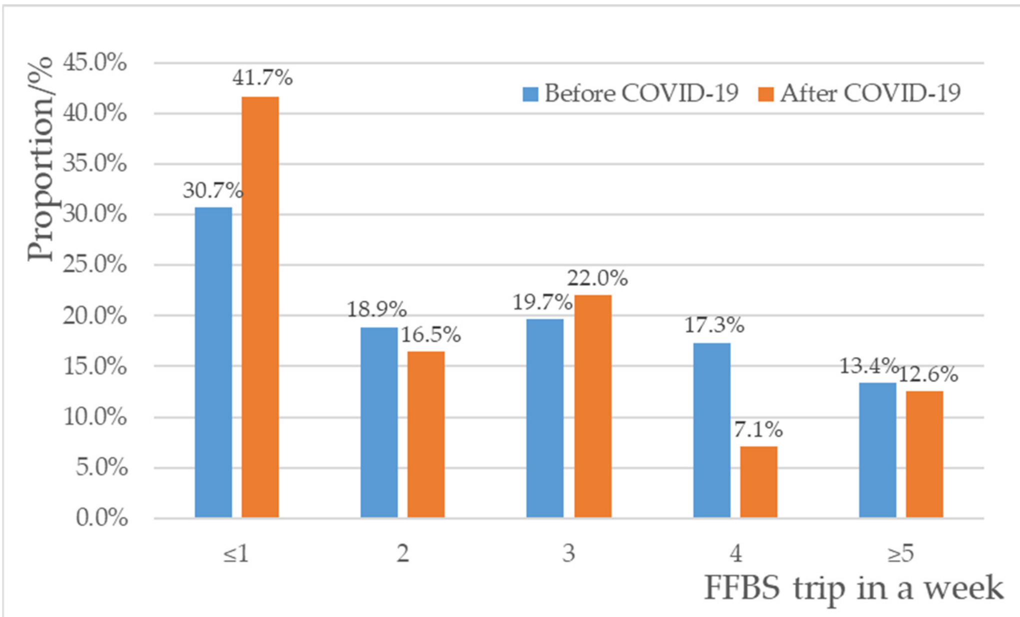

Figure 2. Proportion of weekly trip frequency of FFBS users before and after COVID-19.

4.2. Travel Distance and Duration of FFBS Users before and after COVID-19

A comparison of the proportion of travel distance of FFBS users before and after the pandemic is shown in Figure 3. Most travel distances of FFBS users were less than 3 km, which is within the advantageous travel distance range of bicycle travel. The proportion of long-distance trips which were greater than or equal to 10 km by FFBS was very small. In addition, after COVID-19, the proportion of short distance trips by shared bikes increased while the number of long-distance trips decreased compared with the pre-pandemic period. A possible explanation for this might be that people's cross-regional mobility has been restricted during the pandemic period, most short distance trips are made in residential areas, and FFBS may be chosen as substitution of bus and subway for short-distance trips.

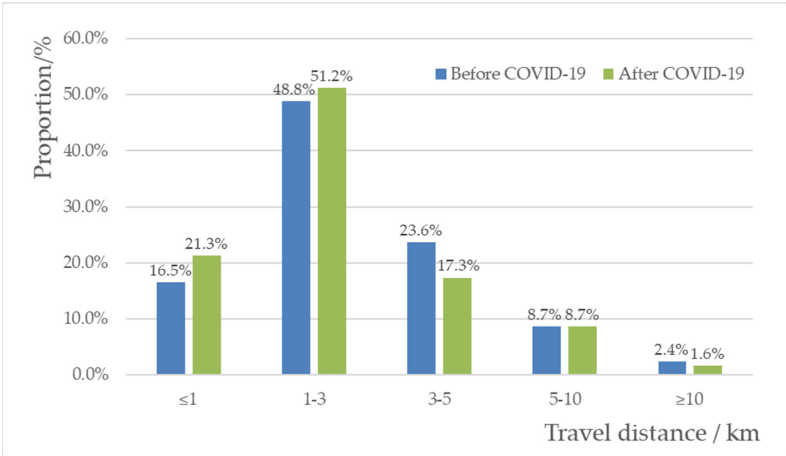

Figure 3. Proportion of trip distance of FFBS users before and after COVID-19.

The travel time distribution of FFBS users before and after the pandemic is shown in Figure 4. The travel time of FFBS trips was concentrated within 20 min. From the perspective of a 15-minute city concept, FFBS could bring convenience to the daily travel of citizens to reach neighboring facilitates, such as shopping, medicining, schooling, and commuting in the restricted context of pandemic [39–41]. After the pandemic, short trips within 5 min increased the most (13% before COVID-19 and 29% after COVID-19), and trips within 10–20 min decreased the most (57% before COVID-19 and 43% after COVID-19). The results are consistent with the change of trip distance in Figure 3, at the normal cycling speed of 5 min per kilometer, the proportion of the travel within 1 km (about 5 min) increases, while in the range from 3 km to 5 km (about 15 to 25 min) decreased.

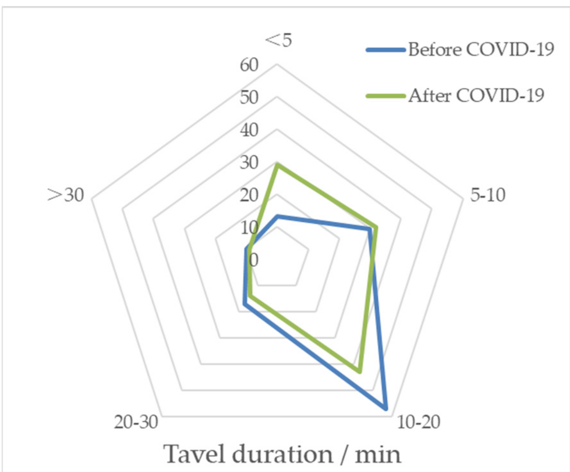

Figure 4. Proportion of trip duration of FFBS users before and after COVID-19.

5. Method

5.1. Ordered Logit Model

The ordered logit model is applicable to cases where the dependent variable is ordered multiple categories (such as the trip frequency in a week in this study, the degree of acceptance, the degree of satisfaction) [42–44]. The ordered logit model containing J $(j = 1, 2, \ldots, J)$ levels of ordered dependent variables is as follows:

$$\ln \frac{P(Y \leq j|X)}{1 - P(Y \leq j|X)} = a_j + \sum_{k=1}^{K} \beta_k x_k \quad (1)$$

where X is the set of independent variables including the attitudes, travel attributes, and individual attribute variables of FFBS users; Y is the set of dependent variables, i.e., weekly travel frequency of FFBS users before and after the pandemic; a_j is the intercept of the level j, $j = 1, 2, \ldots, J$; β_k is the regression coefficient of the kth independent variable; x_k is the kth independent variable, $k = 1, 2, \ldots, K$; $P(Y \leq j|X)$ is the cumulative probability, and $\sum_{j=1}^{J} P(Y \leq j|X) = 1$.

The ordered logit model can be expressed as follow:

$$P(Y \leq j|X) = \exp(a_j + \sum_{k=1}^{K} \beta_k x_k) / \left[1 + \exp(a_j + \sum_{k=1}^{K} \beta_k x_k)\right] \quad (2)$$

5.2. Variable Calibration and Model Building

The influential factors of travel frequency of FFBS users before and after COVID-19 are different. The dependent variables of travel frequency, as once or less a week, twice a week, three times a week, four times a week, five or more times a week, were coded as 1, 2, 3, 4, and 5 respectively. As shown in Table 2, the main factors influencing the travel frequency of FFBS users can be divided into travel attributes, attitudes, and basic individual attributes.

Table 2. Calibration and definition of variables.

Items	Variables	Definition and Notes
Travel attribute	Substituted modes—Walking/Private bike/Public bike/E-bike/Illegal motor taxi/Others	Yes = 1 No = 0
	Substituted modes—Bus/Subway	Yes = 1 No = 0
	Substituted modes—Private car/Taxi	Yes = 1 No = 0
	Travel motivation—Commuting	Yes = 1 No = 0
	Travel motivation—Non-commuting	Yes = 1 No = 0
	Travel duration (min)	Continuous variable
	Travel distance (km)	Continuous variable
	Travel time—Workday—peak hours	Yes = 1 No = 0
	Travel time—Workday—non-peak hours	Yes = 1 No = 0
	Travel time—Weekend/Holidays	Yes = 1 No = 0
	Geographic space	Urban core area = 1 Suburbs = 2

Table 2. *Cont.*

Items	Variables	Definition and Notes
Attitudes and perceptions	Easy to park and pick up	Strongly disagree = 1 Relatively disagree = 2 Not sure = 3 Relatively agree = 4 Strongly agree = 5
	Low travel cost	Strongly disagree = 1 Relatively disagree = 2 Not sure = 3 Relatively agree = 4 Strongly agree = 5
	Convenient payment	Strongly disagree = 1 Relatively disagree = 2 Not sure = 3 Relatively agree = 4 Strongly agree = 5
	High security	Strongly disagree = 1 Relatively disagree = 2 Not sure = 3 Relatively agree = 4 Strongly agree = 5
	High amenity	Strongly disagree = 1 Relatively disagree = 2 Not sure = 3 Relatively agree = 4 Strongly agree = 5
Basic attribute	Gender	Males = 1 Females = 2
	Age	Teenagers ($\leq$18) = 1 Adult (19~40) = 2 Middle-aged (41~65) = 3
	Educational level	Middle school or below = 1 Senior high school = 2 Undergraduate = 3 Graduate or above = 4
	Occupation	Student = 1 Government officer = 2 Enterprise employee = 3 Teacher = 4 Retiree = 5 Others = 6
	Monthly income (CNY)	<3000 = 1 3001–6000 = 2 6001–10,000 = 3 >10,000 = 4
	Possess urban household registration	Yes = 1 No = 2
	Possess driving license	Yes = 1 No = 2
	Public bike IC card ownership	Yes = 1 No = 2
	Number of household bike(s)	0 = 1 1 = 2 2 = 3 $\geq$ 3 = 4
	Number of household e-bike(s)	0 = 1 1 = 2 2 = 3 $\geq$ 3 = 4
	Number of household car(s)	0 = 1 1 = 2 2 = 3 $\geq$ 3 = 4

The modeling process of the ordered logit model is shown in Figure 5. Before establishing ordered logit models, all variables were defined and calibrated [45], the results are shown in Table 2. Second, independent variables with strong correlation were excluded by collinearity tests. Third, two ordered logit models were established to carry out the parameter estimation. Finally, the accuracy of established models was determined by the value of pseudo-R square.

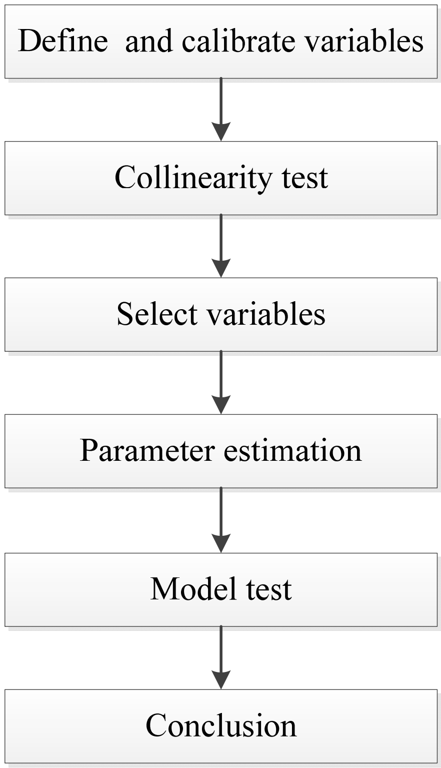

Figure 5. Modeling process of the ordered logit model.

6. Results and Discussions

This paper establishes two ordered logit models for the weekly trip frequency of FFBS users before and after the pandemic, and the results are shown in Table 3.

Table 3. Estimation results of ordered logit models.

Variable	Before COVID-19		After COVID-19	
	B	S.E.	B	S.E.
Preferences				
Easy to park and pick up	0.456	0.298	0.161	0.318
Low travel cost	0.171	0.32	0.886 **	0.385
Convenient payment	0.073	0.318	−0.58 *	0.352
High security	0.272	0.328	−0.42	0.378
High amenity	0.258	0.255	0.588 **	0.29
Basic attribute				
Age	0.18	0.68	−1.389 *	0.762
Educational level	0.192	0.352	−0.103	0.417
Monthly income (CNY)	−0.059	0.18	0.008	0.21
Number of household bike(s)	0.4	0.28	0.233	0.278
Number of household e-bike(s)	−0.017	0.256	−0.165	0.274
Number of household car(s)	−0.162	0.299	0.402	0.331
Male	0.859 *	0.488	0.6	0.474
Female	0 [a]	.	0 [a]	.
Student	−0.784	0.653	−1.001	0.765
Government officer	0.604	0.873	1.712 **	0.874
Enterprise employee	0.436	0.635	1.317 *	0.722
Teacher	0.91	1.128	1.477	1.197
Retiree	−17.667	0	−17.255	0
Others	0 [a]	.	0 [a]	.

Table 3. *Cont.*

Variable	Before COVID-19		After COVID-19	
	B	S.E.	B	S.E.
Possess urban household registration—Yes	0.776 *	0.466	0.527	0.524
Possess urban household registration—No	0 [a]	.	0 [a]	.
Possess driving license—Yes	−0.464	0.526	−0.236	0.571
Possess driving license—No	0 [a]	.	0 [a]	.
Public bike IC card ownership—Yes	−0.344	0.452	−0.998 **	0.506
Public bike IC card ownership—No	0[a]	.	0[a]	.
Travel information				
Travel duration(min)	0.958 ***	0.229	1.109 ***	0.244
Travel distance(km)	−0.018	0.044	−0.057	0.1
Geographic space—Urban core area	0.039	0.493	0.444	0.57
Geographic space—Suburbs	0 [a]	.	0 [a]	.
Substituted modes—Walking/Private bike/Public bike/E-bike/Illegal motor taxi/Others—No	0.543	0.479	0.399	0.574
Substituted modes—Walking/Private bike/Public bike/E-bike/Illegal motor taxi/Others—Yes	0 [a]	.	0 [a]	.
Substituted modes—Bus/Subway—No	−0.24	0.452	−1.158 *	0.595
Substituted modes—Bus/Subway—Yes	0 [a]	.	0 [a]	.
Substituted modes—Private car/Taxi—No	−0.441	0.505	−0.037	0.469
Substituted modes—Private car/Taxi—Yes	0 [a]	.	0 [a]	.
Travel motivation—Commuting—No	−0.241	0.554	0.725	0.74
Travel motivation—Commuting—Yes	0 [a]	.	0 [a]	.
Travel motivation—Non-commuting—No	0.021	0.483	0.744	0.672
Travel motivation—Non-commuting—Yes	0 [a]	.	0 [a]	.
Travel time—Workday-peak hours—No	−1.119 **	0.559	−2.316 ***	0.882
Travel time—Workday-peak hours—Yes	0 [a]	.	0 [a]	.
Travel time—Workday-non-peak hours—No	−0.688	0.609	−3.576 ***	0.937
Travel time—Workday-non-peak hours—Yes	0 [a]	.	0 [a]	.
Travel time—Weekend/Holidays—No	−0.689	0.598	−2.267 ***	0.826
Travel time—Weekend/Holidays—Yes	0[a]	.	0[a]	.
Cox and Snell	0.469		0.549	
Nagelkerke	0.490		0.583	
McFadden	0.202		0.281	

Note: *** $p < 0.001$; ** $p < 0.05$; * $p < 0.01$. [a] denotes that this category of the variable is redundant, therefore it is set to zero.

As for the results of parallel line test of ordered logit models, the chi-square values of the two models are 59.789 and 90.803, respectively, and the significance level p is greater than 0.05 for both, meaning that the parallel line test is passed and the ordered logit models could be used in the current research. For the fitting information of the ordered logit models, the Chi-square values of the likelihood ratio test were 77.759 and 97.101, respectively, and the significance level p-values are both 0.000 (<0.05), indicating that the explanatory power of the ordered logit models is far superior to that of the zero models (the models containing only intercept terms), and the models established are fit well [46,47].

In order to further demonstrate the applicability of the ordered Logit model, this study also established two linear regression models, the results are shown in Table A1. The overall positive and negative effects of coefficients and the significance of independent variables as for linear regression model and ordered Logit model were roughly similar. For the model fitting effects, the R-square of two linear regression models were 0.444 and 0.471, and the pseudo-R square (Cox and Snell) of the two ordered logit models were 0.469 and 0.549, respectively. Hence, we chose the ordered logit models to explain the mechanism of the weekly trip frequency of FFBS users before and after the pandemic in the following.

The results of the ordered logit models are shown in Table 3. In terms of attitudes and perceptions variables, the low travel cost had a significantly positive impact on weekly trip frequency of FFBS users after the pandemic. Compared with ride-hailing, taxi, and other travel modes, the travel cost of FFBS was more acceptable to most people, therefore, it is more suitable to replace the previous journey of public transport. After the pandemic, the positive influence of the high amenity variable became significant and greater than that before the pandemic. COVID-19 is mainly transmitted through the air, and keeping a safe distance from others is an effective means to avoid infection. The importance of ventilation of transportation vehicles was stressed during the pandemic, and FFBS which is used in an open environment could meet the comfort requirements of users physically and psychologically.

In terms of personal attributes, the variable of age had a significantly negative effect after the pandemic. It is understandable that the latent risk of infection of FFBS is high due to its sharing characteristic (because disinfection after usage is not in time), and the elderly are more sensitive to the possibility of infection risk. Before the pandemic, men used FFBS more frequently than women in a week, but after the pandemic, the influence of gender variables was no longer significant. This is probably due to women having a higher aversion to risk and lacking confidence in cycling safety; before the pandemic, women deemed that public transport was safer and more reliable than shared bikes and therefore they were more inclined to choose public transport [37]. However, during the pandemic, considering the high infection risk and the decrease of safety and reliability of public transport, the gap of cognition on the safety of shared bikes between male and female narrowed. The variable of government officer and enterprise employee had a significantly positive impact on the weekly trip frequency of FFBS users after the pandemic. The influence of possessing urban household registration was significant before the pandemic but insignificant after the pandemic. As for the variable of urban public bicycle IC card, the negative effect was significant after the pandemic, indicating that IC card holders have lower frequency of FFBS trips in a week. This is mainly because the similarity between the service of urban public bicycle and FFBS to some extent, users possessing IC cards may choose public bicycles preferentially in some conditions.

In terms of travel attributes, there was a significant positive effect between travel time and the usage frequency of FFBS, suggesting that the longer the trip distance, the more frequently the FFBS was used. Despite the results of the analysis of travel characteristics in Figures 3 and 4 showing that compared to the pre-pandemic period, the overall travel distance and travel duration decreased after the pandemic, many passengers were willing to use FFBS for the entire commute or for longer trips for leisure and recreation, rather than just for the last few miles after the pandemic [6,48]. After the pandemic, the variable "whether use FFBS to substitute for bus and subway" had a significant impact on the weekly travel frequency of FFBS users. Users who used FFBS as a substitution for the bus and subway had a higher travel frequency in a week. A possible explanation for this might be that FFBS not only plays an alternative role to other transportation modes in short-distance travel, but also plays a complementary role to public transportation in long-distance travel [9]. Before the pandemic, the complementary role was more important than the substitutive role, but during the pandemic period, the substitution role of FFBS for public transport trips is enhanced [15]. During the pandemic period, FFBS provided more independent and longer-distance services, not just the integrated service of the FFBS and subway or other public transportation [22]. As for the travel time period, before the pandemic, only the variable of traveling in peak hours of the weekday had a positive impact on the trip frequency of FFBS users, which may be because many trips in peak hours have higher requirements for punctuality, and commuting by bicycle can avoid congestion. During the pandemic, in addition to the peak hours of working days, the travel during off-peak hours of working days, and weekends and holidays also had a significantly positive impacts on trip frequency of FFBS users, probably due to the increase in the amount of exercise and leisure trips during this period [16].

7. Conclusions

This study aimed to explore the influential factors of the weekly trip frequency of FFBS users before and after the pandemic using questionnaire data collected in Nanjing, China. Firstly, demographic characteristics, trip frequency, trip distance, and trip duration of FFBS users before and after the pandemic were analyzed. Then, two ordered logit models were established to compare the factors affecting the weekly travel frequency of FFBS users during these two periods. The results were as follows: (1) The attitude perception variables of low price and travel comfort had a significant impact during the pandemic; (2) travel time had a positive impact on the weekly trip frequency of FFBS users, possibly because compared with the period before the pandemic, many passengers after the pandemic were willing to use shared bikes for long trips such as recreation and commuting tips rather than just for the trips in the last mile; (3) users who used shared bikes to replace public transport during the pandemic period traveled more frequently in a week, and shared bikes may become an alternative to public travel during major health events; (4) women and the elderly have low participation in FFBS trips.

The results in this study could provide theoretical support for the operation and management of shared bikes in the event of similar large-scale health crises. According to the research results, we propose the following countermeasures and suggestions for the healthy development of FFBS during the pandemic. (1) The results show that the travel time has a positive impact on the weekly trip frequency of FFBS users after the pandemic. Bike-sharing enterprises could cooperate with the government and take into account the reduction of the charge standard for long-time usage of FFBS, so as to encourage medium and long-distance FFBS trips and reduce the shift of public transport travelers to private cars. In addition, bike-sharing enterprises should increase the frequency of inspection and maintenance to reduce the loss of shared bikes due to the long-time usage. (2) Individuals' attitude towards the comfort level has a positive correlation with the trip frequency of FFBS users. To improve users' riding comfort perception, on the one hand, improve the riding environment and increase greenway facilities. On the other hand, choose a bicycle that is ergonomic, lightweight, and with low riding resistance. (3) A positive correlation was found between the variable of off-peak working hours and holidays and FFBS trips. Because the trips in these two periods are mostly for recreation purposes, maybe adding more shared bikes in these periods in outdoor recreation areas such as public parks, green spaces, and squares is an effective solution. (4) As the model indicates, users who use FFBS as a substitute for public transportation travel more frequently in a week. The role of bike sharing has changed from short-distance travel and connecting with public transport before the pandemic to replacing part of public transport trips and undertaking complete travel trips during the pandemic. During the pandemic period, the shared bikes could be appropriately increased in public transport stations, residential areas, office areas, and other endpoints of the travel chain. (5) Finally, the results show that there is a low participation rate of FFBS of women and the elderly. When planning and placing relevant facilities, it is necessary to pay attention to the travel needs of these vulnerable groups (women, the elderly, and low-income groups) and simultaneously promote the equity of active transportation. It might reconsider the allocation of road space, and appropriately add separate bike lanes separated from motor lanes to ensure cycling safety given that women and the elderly could be more concerned about the cycling safety.

The limitations of this study are as follows: (1) This paper conducted a survey based on the background of Nanjing, China, but the severity of the pandemic in each city is different, and the corresponding pandemic prevention measures are also different (lockdown, mandatory telecommuting, etc.), which may lead to different research results. Therefore, further studies based on the background of other cities are needed. (2) We adopted a structured questionnaire survey to investigate the factors affecting the frequency of FFBS users before and after the pandemic, including personal attributes, travel attributes, attitudes, and perceptions related to the usage of FFBS. The information obtained from the structured survey was limited; hence, unstructured interviews to expand and deepen the knowledge of this issue in the future are worth further exploring. (3) Respondents over 65 years old who participated in the survey are few; the possible reason for this is that this group has weaker physical functions and fewer people would choose FFBS for travel. Nevertheless, the influential factors of usage of FFBS for this group are still worth further exploration. (4) The comparison of FFBS users' trip frequency before and after the pandemic are discussed in this study, future studies may consider all active travel modes as a whole object, including walking, public bicycles, bike sharing, and electric bike sharing, to explore the changes and the influential mechanism of users' travel frequency before and after the pandemic.

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Appendix A

Table A1. Estimation results of linear regression models.

Variable	Before-COVID-19		After-COVID-19	
	B	S.E.	B	S.E.
Preferences				
Easy to park and pick up	0.204	0.187	0.08	0.176
Low travel cost	−0.06	0.205	0.366 *	0.197
Convenient payment	0.054	0.201	−0.178	0.182
High security	0.146	0.208	−0.11	0.206
High amenity	0.101	0.162	0.181	0.163
Basic attribute				
Age	0.213	0.428	−0.513	0.424
Educational level	0.168	0.22	0.088	0.211
Monthly income (CNY)	0.006	0.11	0.118	0.105
Number of household bike(s)	0.358 **	0.162	0.241	0.154
Number of household e-bike(s)	−0.072	0.157	−0.088	0.148
Number of household car(s)	−0.11	0.185	0.196	0.179

Table A1. *Cont.*

Variable	Before-COVID-19		After-COVID-19	
	B	S.E.	B	S.E.
Gender	−0.347	0.291	−0.031	0.263
Occupation	0.045	0.08	0.038	0.078
Possess urban household registration	−0.391	0.286	−0.194	0.284
Possess driving license	0.171	0.334	−0.067	0.314
Public bike IC card ownership	−0.003	0.275	0.162	0.269
Travel information				
Travel duration (min)	0.525 ***	0.131	0.452 ***	0.115
Travel distance (km)	−0.026	0.025	0.001	0.058
Geographic space	−0.042	0.302	−0.143	0.296
Substituted modes—Walking/Private bike/Public bike/E-bike/Illegal motor taxi/Others	−0.373	0.307	−0.462	0.327
Substituted modes—Bus/Subway	0.106	0.284	−0.005	0.305
Substituted modes—Private car/Taxi	0.182	0.315	−0.267	0.267
Travel motivation—Commuting	0.146	0.333	−0.1	0.409
Travel motivation—Non-commuting	0.074	0.305	−0.093	0.378
Travel time—Workday—peak hours	0.793 **	0.362	1.499 ***	0.497
Travel time—Workday—non-peak hours	0.392	0.382	1.825 ***	0.517
Travel time—Weekend/Holidays	0.558	0.383	1.408 ***	0.463
Constant	−0.003	1.417	−0.106	1.523
R-squared	0.444		0.471	

Note: *** $p < 0.001$; ** $p < 0.05$; * $p < 0.01$.

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