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Modeling the Impact of Dock-less Bike-sharing System on Outpatient Trips

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Abstract:

Better transportation and medical service systems contribute to urban sustainable development. Dock-less bike-sharing system (DLBS) is an innovative, sustainable, and flexible travel mode that has been a worldwide spread. This paper addresses a pioneer research aims to explore the characteristics of DLBS usage in outpatient trips and its impacts on travelers' mode choice behavior. The data sources include the survey at Beijing Friendship Hospital and the trip data from a DLBS company. The research results show that DLBS has evidently decreased the private bike usage by over one third and become a replacement. It is also an important feeder mode for public transport service to the medical service. Among 1,348 DLBS usage in outpatient trips, more than 40% trip transactions are connecting the hospital and public transport stations. Over 70% travelers ride DLBS only in a single trip while having other activity purpose after leaving the hospital. Multinomial Logit (MNL) model is used to investigate the factors that influence the DLBS daily usage. Education and online payment have positive affect. This study can be extended to DLBS usage in other trips with similar characteristics such as appointment-based, short-duration, and multiple activities.

Keywords: Dock-less bike-sharing (DLBS), Outpatient trip, Multinomial Logit (MNL) Model, Survey data, Trip data.

1. Introduction

Public facilities, such as hospitals and clinics, are essential resources and services for a citizen's daily life. Unlike emergency patients who need immediate treatment, outpatients are advised to make appointments in advance via smartphone application (APP), website, or phone call. They are also required to arrive earlier than the appointment time; otherwise, their treatment will be canceled, and their absence will be recorded. This cancellation may negatively affect their next appointment. Another characteristic of outpatient trips is the short duration. The treatment duration in hospitals usually lasts less than an hour. Outpatients may have various activities in addition to returning home. The trips to hospital only accounts for a part of outpatients' daily trip chain. Similarly, many other activity trips, such as the trips for a movie, a drama, a museum tour, gym or any other courses, and dinner dates, can be appointment event-based, short-duration, and multiple-activity, especially in the era of smart life with the benefit of e-appointment. From a social perspective, understanding and offering door-to-door mode choices for these travelers are necessary. Studies on outpatient trips can be extended to other activity trips.

With the thriving sharing economy and rising environmental awareness, bike-sharing has developed rapidly worldwide. By the end of 2019, more than 2,000 bike-sharing systems have been operated in over 50 countries (Meddin & DeMaio, 2019). In USA, Spin and LimeBike launched dock-less bike-sharing systems (DLBS) with public and political support in 28 cities (National Association of City Transportation Officials, 2018). Dock-based bike-sharing systems (DBBSs) have been implemented in New York City; Washington, D.C.; Paris; London; and many other cities around the world. Since August 2019, the number of DLBSs in China reached 19.5 million. With more than 300 million registered members, the number of bike-sharing daily orders exceeded 47 million (Annual Report on the Development of Shared Mobility in China, 2019). The data from 51 cities in China indicated that the percentage of cycling mode declined annually by 3% since 2000 (Li et al., 2017). After the introduction of DLBS, cycling accounted for a larger proportion than before.

DLBS is a popular travel mode because of its convenience in the widespread distribution, destination accessibility and simplicity of payment (Leister et al., 2018). Compared with DBBS, which requires travelers to rent and return the bikes to dock stations, DLBS can provide better accessibility and availability. Advanced technology has been widely applied in bike-sharing systems for the positioning, operation, and payment (Shen et al., 2018; Shaheen et al., 2013). Given that the location can be tracked by GPS devices attached to the bikes, DLBS offers convenient searching, rental, and automatic unlocking of bikes via smartphone APPs (Chen et al., 2018; Pal, & Zhang, 2017). Some bike-sharing programs have been introduced by hospitals in USA to encourage the staffs and local residents to promote green and healthy travel modes (Reading Hospital, 2020; Healthleaders Media News, 2020). DLBS has been widely used in outpatient trips, leading to excess numbers of DLBS parked around hospitals (Xinhuanet, 2020; Tech.sina.com, 2020). Reasonable management measures are required by related departments and companies to deal with this situation. Under an epidemic situation involving infectious diseases, the willingness of residents to use public transport has significantly decreased. Riding DLBS can reduce person-to-person contact. The utilization rate of disinfected DLBS has increased from 30% in normal times to 50% at present (Tencent News, 2020).

The initial target of this paper is to study the travelers' mode choice behavior in outpatient trips. Consequently, a survey of outpatients was conducted at Beijing Friendship Hospital, Beijing, China in October 2016. After that, the new mode DLBS appeared in November 2016 and quickly got popularized in Beijing. To explore the impacts of DLBS on outpatient trip, the supplementary survey was carried out in October 2017 at Beijing Friendship Hospital for comparative research.

Beijing Friendship Hospital is rated as the highest-level public hospital in China. It serves approximately 8,000 outpatients of all ages daily. Beijing Friendship Hospital operates at 08:00 ~ 12:00 and 13:00 ~ 17:00 on workdays and 08:00 ~ 12:00 on weekends. On-site registration begins an hour earlier than the working hours. Driving to Beijing Friendship Hospital is not recommended because it is located in downtown area, as shown in Figure 1 (a). There is normally a high risk of traffic congestion and lacks parking spaces. During commuting peaks in 2017, 26% of Chinese cities were congested (Amap.com, 2020). Given the lack of parking spaces around Beijing Friendship Hospital, the private car drivers often have to spend more than half an hour to find a parking spot. Moreover, public transport cannot provide sufficient accessibility. Although three subway stations are located around Beijing Friendship Hospital, it will take more than 15 minutes for a healthy adult to walk from the subway stations to Beijing Friendship Hospital. DLBS is densely distributed in this area, as shown in Figure 1 (b) (Baidu map). Providing another mode choice option for outpatients is necessary.

(a) (b)

Figure 1. (a) Location of Beijing Friendship Hospital in urban area. (b) Dock-less bike-sharing around Beijing Friendship Hospital.

To the best of our knowledge, there is a research gap that studies on DLBS usage in specific activities are rare, especially when those that involve outpatient trips. Hence, this study aims to fill this gap. The main contributions include but are not limited to the following:

1) On the basis of the survey data (n_1 = 1,047) in 2016 and 2017 and DLBS trip data (n_2 = 1,348), the impacts of DLBS on the travel behavior of outpatients was explored for the first time. The changes in active travel mode choice in outpatient trips were investigated comparatively. The results indicated that DLBS had partly replaced private bike and became a feeder for public transport service.

2) The travelers' preferences for alternative travel modes were analyzed based on the quantitative evaluation of trip experiences in different travel modes. The factors that influence the daily usage of DLBS were explored using the Multinomial Logit (MNL) model. The general characteristics of DLBS users were explored to further understand this novel travel mode.

3) To study the DLBS usage pattern, a fortnight DLBS trip dataset was used as data source. The transactions of specific-activity trips were extracted from trip data. The spatial and temporal characteristics of outpatient trips and the role of DLBS in multi-activity trips were studied.

The remainder of this work is organized as follows. Section 2 presents a review of recent studies on DBBS, DLBS and outpatient trip. Section 3 introduces the datasets and methodology used in this study. Section 4 addresses the detailed results about the impact of DLBS on outpatient trips. Section 4 is the discussion. The last section presents the conclusions.

2. Literature Review

2.1 Dock-Based Bike-Sharing System

Bike-sharing system is a healthy, convenient, and emission-free travel mode. Matching the people's travel demand is an important research topic in DBBS. Studies on DBBS are mainly aimed to explore the influence of DBBS on other modes and predict the capacity of dock stations.

a. Influence on other modes

DBBS universally reduced the private car and taxi use, increased cycling mode in most cities, and had significant impacts on the public transport system (Shaheen et al, 2013). When used in combination with the subway, DBBS provided convenient trip experience and could relieve traffic congestion especially for commuters (Manzi & Saibene, 2018; Ji et al. 2016). In Brisbane, Australia, 21% of bike-sharing users reduced their private car usage frequency after the implementation of CityCycle. The Melbourne bike-sharing system decreased driving by 19% (Fishman, 2015). Universal results could be found in Germany, Austria, and Switzerland (Buehler et al., 2016). Campbell and Brakewood (2017) emphasized that understanding the correlation of DBBS and public transport service was vital in planning a sustainable transport network. A natural experiment implemented in New York City, USA found that DBBS replaced the bus trips. The travel behavior of non-registered members of bike sharing system was also affected, especially the private bike owners. According to the data in Washington, D.C., and Minneapolis, USA, Martin and Shaheen (2014) studied the changes of the share of public transport after DBBS got into operation. The findings showed that in core urban area with high population density, DBBS had attracted part of public transport users in short-distance trips due to the advantages of fastness and cheapness. Based on the location data of dock stations and bus systems in Hangzhou and Ningbo, China, Yang et al. (2018) established a multilayer coupling network model that considered geographical information of the DBBS stations, the bus stations, and the bus routes. Results showed that DBBS significantly improved the network efficiency of urban public transport system. McBain and Caulfield (2018) found that the dock stations were closely integrated with public transport stations and led to better travel efficiency. DBBS could improve the service range of subway stations and had attracted a large part of subway passengers in transfer trips (Cheng & Lin, 2017; Qin et al, 2018). Based on the DBBS data in Cork, Ireland, Lahoorpoor et al. (2019) analyzed the spatial and temporal patterns of DBBS usage according to more than 500,000 origin-destination (OD) transactions in Chicago, USA. The riding distance of approximately 80% bike-sharing trips were less than 3.5 km. The numbers of DBBS usage in the morning peak hours on most workdays were higher than those in the evening peak. Additionally, the remarkable variation in impact of different user groups and behavior patterns caused difficulty in DBBS operation. The peak usages of CityCycle on workdays demonstrated a triple peaks with significant morning and evening peaks and small noon peak (Mateo-Babiano et al., 2016).

b. Capacity prediction

Tang et al. (2018) calculated the minimum scale of dock stations to guarantee the DBBS availability near each public transport station by considering the integration of DBBS with public transport service. This strategy reduced the required dock station scale by 39% ~ 75% via Monte Carlo simulation. Lin et al. (2018) constructed a graph convolutional neural network for the hourly station-level demand prediction in a large-scale DBBS network with a data-driven graph filter model. The CitiBike dataset in New York City was tested. Yang et al. (2019) proposed a prediction model considering the travel demand and dock station capacity. According to the prediction results, the rebalancing strategy was enhanced, and the out-of-service time decreased by 86% compared with the former. Their results showed good accuracy on the Hangzhou DBBS dataset. Huang et al. (2019) designed a bimodal Gaussian inhomogeneous Poisson algorithm to predict the available numbers of bikes and docks. The designed algorithm was evaluated using the Bay Area and Hubway DBBS datasets, and the experiment results showed better effects than traditional methods. By using the taxi trajectory data in Seoul, Korea, Park and Sohn (2017) proposed p-median and maximum coverage location problem models to determine the reasonable location of dock stations. These methods contributed to the reduction of private car usage in short-distance trips and subsequent environmental benefits.

2.2 Dock-Less Bike-Sharing System

Flexibility is an important and attractive characteristic of DLBS. DLBS can provide better flexibility in bike access and usage than DBBS. DLBS users can avoid the risk of full/empty dock stations and park the bikes anywhere, thereby solving the first and last mile problem. DLBS have no installation cost on dock stations and have lower cost per bike than their DBBS counterpart (Mooney, 2019). DLBS has influenced the multimodal transport and changed the travel mode choice of residents.

a. Travel behavior

Using trip data of both DBBS and DLBS in Nanjing, China, Ma et al. (2020) comparatively studied the travel characteristics and influence factors of DBBS and DLBS. They found that DLBS usage had a shorter travel distance and higher volume than DBBS. Compared with DBBS, DLBS was more widely used in the trips to entertainment points of interest by young people. DLBS was mainly used in trips characterized by short duration (less than 15 minutes) and short-middle distances (less than 3 km). The significant impacts of the popularity of DLBS on the DBBS market share confirmed the superiority of DLBS.

Zhang et al. (2018) constructed transition matrices by using the trip data in Zhongshan, China to explore the role of DLBS in multimodal trips. The researchers found that two-thirds of DLBS trips were a part of multimodal travel chains, in which DLBS was used from public transport stations to the users' home or workplace. Using 739 survey data in Beijing, China, Zhao and Li (2017) suggested that riding distance was a key factor in DLBS transfer trips that connected subway stations and home or workplace. On the basis of the Mobike data in Nanjing, China, Li et al. (2019) categorized the subway stations by using K-means clustering to explore the activity patterns, spatial distribution, and influential range of the DLBS system around subway stations. Lin et al. (2019) established the bike buffer zone of subway station based on DLBS track data. They found that the coverage ratio and overlap degree of buffer zone increased significantly in urban area. To monitor the DLBS parking intensity around the subway stations, Xu et al. (2019) presented a novel dynamic time warping clustering method and estimated the early warning index. Ma et al. (2019) estimated a score matching-based statistical method to evaluate the relationship between DLBS and public transport by using the data of bus transit, DLBS trip, and place of interest from 2016 to 2017 in Chengdu, China. The increase in DLBS usage caused the evident growth in bus usage on the AM and PM peak hours during workdays. This finding revealed that commuting demand was a key factor of DLBS and buses. Zhang and Zhang (2018) investigated the associations between public transport and DLBS usages in the USA and found that frequent bike-sharing usage increased by 1.4% in each unit of public transport. Li et al. (2019) demonstrated that DLBS caused a 5.93% reduction in DBBS usage in London, England. Guo et al. (2021) studied the influence of built environment on the integration between DLBS and subway. The findings revealed that the number and length of cycling paths around subway stations had positive correlation to the integrated usage of DLBS and subway. In May 2017, a survey with 1,180 samples was conducted to investigate the travel mode choice before and after launching DLBS in the Shanghai, China market. After the launch of DLBS, Jia and Fu (2019) found a significant increase in bike usage in both commuting (from 21.9% to 30.9%) and non-commuting trips (from 22.1% to 33.6%).

Logit model is commonly used in survey-based studies about DLBS mode choice behavior. According to 623 survey data, Campbell et al. (2016) used the MNL model to analyze the DLBS choice in Beijing, in which the impacts on air pollution were considered in the questionnaire. On the basis of 4,939 questionnaires in Nanjing, China, Du and Cheng (2018) established a MNL model to investigate the influence factors and travel characteristics of DLBS usage in different patterns, including OD, travel cycle, and transfer patterns. According to 595 survey data in Nanjing, China, Du et al. (2019) investigated the influence factors of DLBS and other travel modes by using the MNL model. The results showed that four-fifths of DLBS trips were mostly used for medium-distance (less than 5 km) trips. DLBS is an alternative mode that attracted the attention of walking travelers (39%), private bike users (15%), and bus passengers (14%). Habib (2018) used a heteroskedastic polarized logit model to analyze the cycling choice in Canada. The results of this study showed that cycling had evident appropriateness and superiority over walking and motorized modes in medium-distance trips.

b. Environment benefits

Environmental factors including poor air quality are calling for the switch from motor modes to active modes (Li & Kamargianni, 2018). The bike-sharing has triggered significant environmental benefits, and is good for public health (Eren & Uz, 2020; Cai et al, 2019; Fishman, Washington, & Haworth, 2013). On the basis of Mobike trip data in Beijing, China, Cao and Shen (2019) found that DLBS contributed to the reduction of CO_2 emission and played positive roles for sustainable environment. Zhang and Mi (2018) demonstrated the remarkable potential of DLBS in reducing energy consumption and emissions. In 2016, DLBS saved 8,358 tons of petrol consumption and 25,240 tons of CO_2 emissions in Shanghai, China. Chevalier et al. (2019) analyzed the riding acceptance according to 1,131 respondents of five campuses in Shanghai, China. The riding acceptance and trip experience remarkably increased due to DLBS.

As a new travel mode, DLBS has caused new problems including the bicycle theft, the vandalism, the sidewalk occupation, and the landscape deterioration (Sun, 2018; Shi et al., 2018, Bielinski et al., 2020). The occupation of road resources caused by DLBS near the hospitals will result in serious consequences and has received hospitals' attention. Meanwhile, the usage of bike-sharing was significantly affected by build environment and weather. Sun et al. (2018) summarized the failure of Pronto bike-sharing system in Seattle, USA. The commercial area, adverse weather condition, and hilly terrain negatively affected bike-sharing usage. On the basis of the survey in cold areas in USA in 2015 and 2016, the expected bike-sharing usage in winter accounted for only 10% - 30% of that in summer. More than half of the bike-sharing system ceased operating in winter (Godavarthy & Taleqani, 2017). The measures to improve and ensure the DLBS sustainability have become a hot research topic. Based on 8,813 social media data from April 2016 to December 2017, Yin et al. (2019) pointed out that credit reward regulations should be provided to reward customers with positive activities, such as riding the bikes from unreasonable areas to recommended areas. Jiang et al. (2019) studied the reasons of the disorderly DLBS parking by using 235 questionnaires. The government and DLBS companies were advised to provide reasonable parking regulations and sufficient parking areas with guide signs. Médard de Chardon (2017) stated that it could be ineffective by only increasing the scale of bikes instead of redistributing the public roads source. Médard de Chardon (2019) suggested that due to the lack of clear target, bike-sharing system did not bring the expected benefits to the whole society, but mainly served the privileged urban residents. Successful implementation required conditions including the political will, the costs and the social norms (Firth et al., 2021).

2.3 Outpatient Trip

Compared with other service facilities, public hospitals need adequate and equitable accessibility (Neutens, 2015). Cheng and Chen (2015) analyzed the spatial accessibility of public hospitals in each sub-district based on travel duration and spatial difference in Shenzhen, China. Ghasrodashti and Ardeshiri (2015) identified different influence factors on travel mode choice in the outpatient trips. On the basis of 900 investigations in Shiraz, Iran, the travel mode choice was influenced by both subjective and objective factors, such as the lifestyles of respondents and the parking availability.

By simultaneously considering the environmental, safe, and physical factors, Kamargianni et al. (2015) proposed an integrated choice and latent variable model to analyze the travel mode choice. Based on a survey in Cyprus in 2012, the parking availability was an important factor for both motorized vehicle users and bicycle riders when choosing alternative modes. Rotaris and Danielis

(2014) investigated a public hospital located near a university in Italy. The researchers found that students were generally willing to drive for the treatments although the public transport system provided good service. Mitra et al. (2017) found similar conditions in downtown Toronto, Canada. Despite the development of cycling facilities, the citizens were unlikely to switch from driving to cycling. However, if a public hospital was located in a dense urban district without enough parking spots, then driving was an uncommon option due to the lack of parking spaces, especially in developing countries.

Previous studies have analyzed the mode choice and travel behavior of bike-sharing users. The merits and demerits of bike-sharing system are also well summarized. The outpatient trips have special travel demands and are vital to residents' daily life. However, there is a research gap on the combination of DLBS and outpatient trips. In terms of the research methods, survey data and trip data are seldom used together in previous researches. In this paper, two kinds of data are jointly used to take the advantages of both. The influence factors and trip characteristics in outpatient trips are analyzed based on the combination of different datasets. The results can be further explored in other short-distance, appointment-based and multi-activity trips.

3. Materials and Methodology

Compared with previous studies, this study aims to discover the impact of DLBS on outpatient trips. To determine the travel demand and outpatient behavior, a stated preference / revealed preference (SP / RP) paper-based interview survey was conducted at the waiting hall of Beijing Friendship Hospital. All the respondents were with mild symptoms and no risk of infection. The respondents could communicate normally and use all types of travel modes. MNL model was used to analyze the influence factors of DLBS usage in daily trips. Furthermore, the origin-destination (OD) pairs in outpatient trips of Beijing Friendship Hospital and Peking University Third Hospital were extracted from a DLBS trip dataset and used to portray the spatial and temporal characteristics.

3.1 Dataset Description

Well-trained investigators were guided to investigate the impact of DLBS in both outpatient and daily trips before and after the implementation of DLBS. The survey was undertaken in Beijing Friendship Hospital with the same condition in October of 2016 and 2017. Survey dates were chosen not on the basis of the day of the week but according to the one day in a week banning policy for the petrol cars in Beijing. The restricted license number turned from Monday to Friday, and they were changed every 13 weeks. On the two survey dates in 2016 and 2017, the restricted license numbers were both 3 and 8. Survey time was determined according to the registration and working hours of Beijing Friendship Hospital on workdays and weekends. The survey information is listed in Table 1. A total of 1,047 valid questionnaires were collected.

Table 1.
Survey information in 2016 and 2017.

	2016		2017	
Survey Date	Oct 13th Thursday	Oct 16th Sunday	Oct 25th Wednesday	Oct 29th Sunday
Survey Time	07:00-17:00	7:00-12:00	7:00-17:00	7:00-12:00
Weather Condition	12°C-22°C Haze, No wind	12-21°C Sunny, No wind	9°C-15°C Cloudy, No wind	1°C-12°C Cloudy, Breeze
Restricted License Plate Number	3,8	N/A	3,8	N/A
Sample Size	347	178	342	180
	525		522	
Total Sample Size	1,047			

Another DLBS trip dataset (Biendata Competitions, 2019) contains the Mobike transactions in entire range of Beijing for 2 successive weeks in 2017. The sample size exceeds 3 million, which is 60% of the total Mobike samples in Beijing during the data time period. The usage of Mobike accounts for about 40% of all DLBS companies in 2017. The transactions of incomplete trip chain and the private information were concealed. During the data period, the weather was good without rainfall. The temperature was between 13 °C and 33 °C, which was suitable for cycling. No important event was scheduled during the data period, so the validity and applicability of data can be guaranteed. The data structure included fields of user ID, order ID, bike ID, trip start time and OD. The description of DLBS trip data is presented in Table 2. The geographic information in this dataset is defined by **GeoHash**. The space is divided into grids with the side length of 153 meters. Each grid is recorded by a specific seven-digit ID of character and number, such as "wx4epe1". Based on the DLBS trip dataset, the spatial and temporal characteristics of DLBS usage are further analyzed. The comparative analysis of survey and DLBS data is also conducted to assess the impact of DLBS on outpatient trips.

Table 2.
Description of the data structure of DLBS trips.

Data Field	Example	Explanation
Order ID	1963473	Unique ID of each trip order
User ID	383583	Unique ID of each traveler
Bike ID	217105	Unique ID of each bike
Bike type	2	Different type of bike
Start time	2017/5/11 9:46	Trip start time. Accuracy of minutes
geohashed_start_loc	wx4erzy	Seven-digit ID with the accuracy of 153 meters
geohashed_end_loc	wx4exb9	Seven-digit ID with the accuracy of 153 meters

3.2 Questionnaire Design

The questionnaire for all respondents contained three sections, namely, the demographics, the daily trips, and the outpatient trips. The demographic section was used to collect information about online map usage, maximum acceptable cycling duration, home ownership of private car and bike, membership with DLBS companies, gender, age, education, and monthly income. The acceptable cycling distance was a separate question in the questionnaire. Respondents answered the numbers directly. In the section of daily trips, information including the frequent trip OD and travel duration in daily life were acquired. The questions on outpatient trips were grouped into three parts, namely, general trip information, experience evaluation, and trip characters based on the travel mode. General-information questions included the appointment time of scheduled treatment, origin, departure time, travel distance, trip duration, and travel mode. The evaluation of outpatient trip experience was recorded with four indexes, namely, the punctuality, the convenience, the satisfaction, and the comfort. A series of questions were asked according to different travel modes. For example, public transport passengers were asked about the waiting time, transfer time, walking distance, and evaluation of crowding by using picture examples of the coach with various load factors. In private car drivers, the questions were designed on the basis of previous works to record the subjective feelings on parking availability, time to find a parking spot, parking cost, and walking distance from the parking lot to Beijing Friendship Hospital. For the taxi and online car-hailing users, the questions involving time and fare costs were similar. However, the parking-related questions were excluded for online car-hailing travelers. Active transport travelers were asked about the travel distance. The satisfaction of DLBS users on the distribution density, the positioning accuracy, the proportion of damaged bicycles, and the riding comfort were recorded. The desire of users to change their travel mode in outpatient trips and preferred alternative mode were the common questions for all the travel modes. Additional questions for registered members of DLBS were listed at the end of the questionnaire. The usage intention of DLBS under different weather, travel distance, travel cost, and road conditions were investigated with options in quantitative details.

3.3 MNL Model

The MNL model is widely used to analyze the relationship between different factors. In this study, this model was used to reflect the probabilities of travel mode choice in daily life while considering the different variables as potential influence factors. The variables in the MNL model including the personal information, the occupation, the demographics, the weather, and the cycling environment were selected from the demographic and the daily trip information of the survey. To show the probabilities in making certain choices, the MNL model of DLBS usage in daily trips were estimated as follows in (1) and (2).

$$P_i = \frac{\exp(U_i)}{\sum_{i=1}^{k} \exp(U_i)} \tag{1}$$

$$U_i = V_i + \varepsilon_i = \theta_1 S_{1i} + \theta_2 S_{2i} + \ldots + \theta_m S_{mk} + \varepsilon_k \tag{2}$$

where P_i is the probability of choosing travel mode i, U_i is the utility of travel mode i, V_i is the random utility term of travel mode i, ε_i is the fixed utility term of travel mode i. S_{mk} is the service attribute m of travel mode k. θ_m is the utility coefficient of service attribute m.

To test the independence from irrelevant alternative (IIA), the Pearson coefficients of these influence factors were calculated. The high-relative variables, such as travel duration and travel distance, were removed to maintain independence. After the above elimination for independence, 13 variables with high significance levels were selected for further investigation on the probability of DLBS choice under different conditions. The MNL model details and results will be presented in the section of results and discussions.

3.4 Extraction of Outpatient Trip

The Outpatients and hospital staffs are the major groups going to hospital area. To extract outpatient trips from the DLBS trip dataset, the data were screened from six aspects, namely, the data cleaning, the location, the departure time, the outpatient identification, the trip interval, and the riding distance. A total of 1,348 transactions were considered as outpatient trips after extraction, in which 1,163 transaction were on workdays and 135 transactions were on weekends, respectively.

1) Data cleaning:

The DLBS transactions inconsistent with the actual situation, such as the lack of data fields, the duplicate order ID, and the OD (represented by geohashed_start_loc and geohashed_end_loc) of one single trip located in the same grid, were deleted.

2) Location

If the origin or destination of a DLBS trip was at the grid where Beijing Friendship Hospital and Peking University Third Hospital located, then it was considered as an outpatient trip. The location (latitude and longitude) of Beijing Friendship Hospital was obtained through Baidu Map. A program was used for the mutual conversion between the GeoHash and longitude-latitude coordinate systems. According to the field investigation, large parts of the DLBS were parked outside the hospital because bikes were not allowed to enter the hospital area. The grids that the hospital located in or which was one of its 8 neighbor grids were regarded as the study area.

3) Departure time

The departure time of outpatient trips should be consistent with the hospital working hours. Otherwise, the trip was not considered for medical treatment. According to the working and on-site registration hours discussed in the Introduction, the screening ranges of departure times (start times) on workdays and weekends are shown in Table 3.

Table 3.
Range of start time.

	Workday	Weekend
Working hour	08:00-12:00; 13:00-17:00	08:00-12:00
On-site registration hour	07:00-11:00; 12:00-16:00	07:00-11:00
Departure time of arrival trips to hospital	06:00-16:30	06:00-11:30
Departure time of departure trips from hospital	08:00-18:00	08:00-13:00

4) Outpatient identification

Unlike the staff in the hospital, outpatients usually do not visit the hospital many times in a week. Hospital staff could also use DLBS in commuting trips. To avoid interfering with the travel characteristics of outpatients, the corresponding transactions of user IDs with trips to Beijing Friendship Hospital more than three times within two weeks were deleted.

5) Trip interval

The time duration of outpatient treatment was considered another extraction criterion. For travelers (identified by the user ID) that chose DLBS both arrival to and departure from hospital, the time interval between the two trips should be consistent with the treatment duration. Transactions with trip intervals of less than 15 minutes and more than 4 hours were filtered.

6) Riding distance

The distributions of riding distance were calculated based on survey data, as shown in Figure 2. A program was established to calculate the riding distance between each OD. Travel distance was the key factor for DLBS usage. DLBS was mostly used in short-distance trips. The riding distance of more than half of the DLBS trips were within 2 km, and over 90% were less than 5 km; these findings were consistent with those of previous studies (Shi et al., 2018; Kamargianni et al., 2015; Caulfield et al., 2017; Bao et al., 2017; Lee et al., 2016; De Souza et al., 2017). Most of the riding distances were within 6 km. 6 km was considered as the screening criterion of the reasonable riding range. Transactions with distances of more than 6 km were deleted.

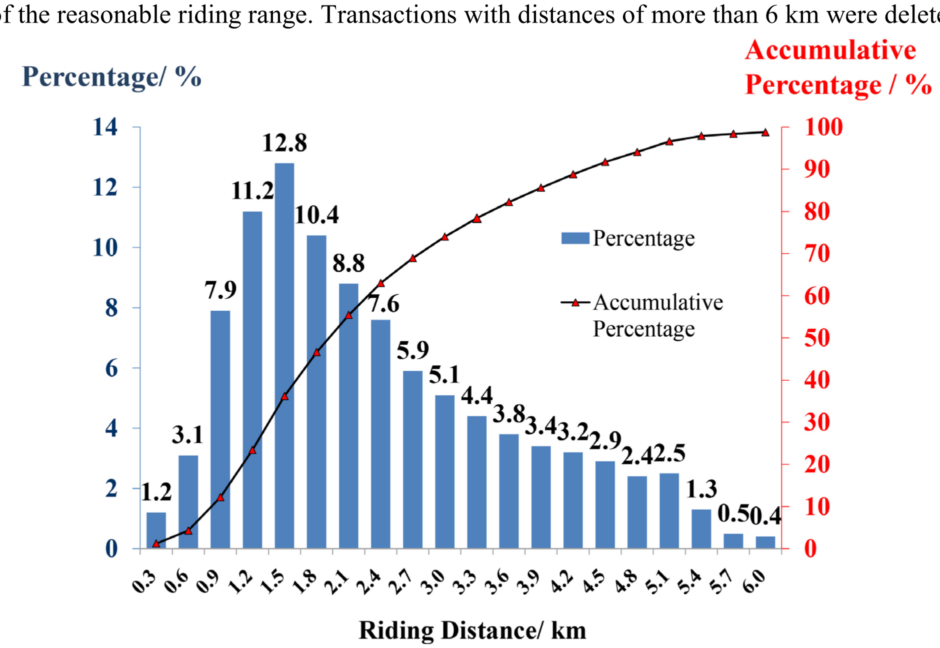


Figure 2. Distribution of Riding Distance in Outpatient Trips.

4. Results and Discussions

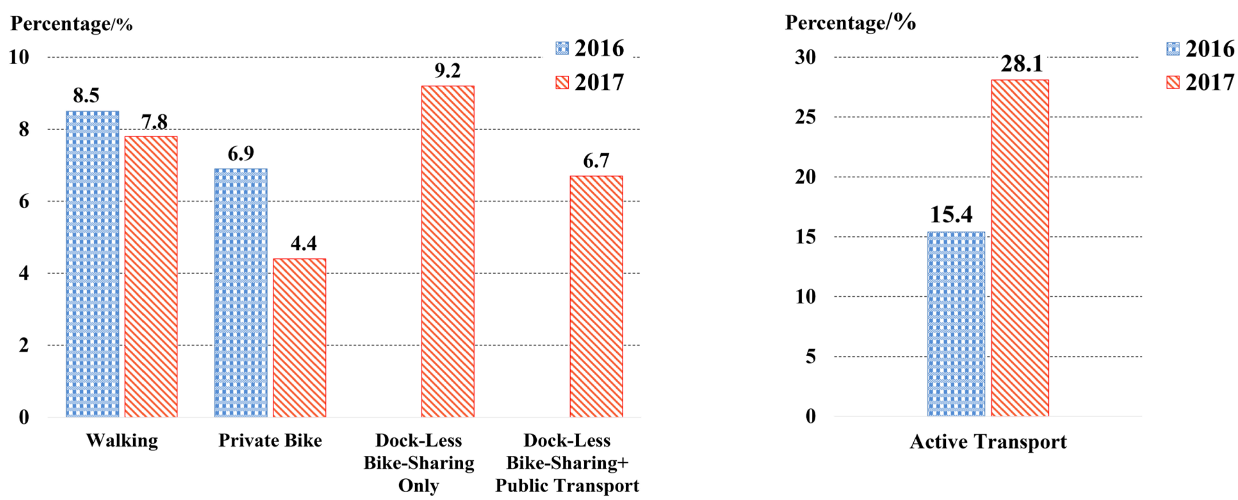
The results from the outpatient trip survey reflected the changes and trip experience in active travel modes. The influence factors of DLBS usage were analyzed using the MNL model on the basis of the demographics and daily trips sections of the survey dataset. Then, the role of DLBS in multimodal travel was further investigated. The spatial and temporal distribution of outpatient trips in the DLBS dataset was explored and then compared with the results from the survey and model. Finally, four types of outpatient trips were classified.

4.1 Choice of Active Travel Mode

The impact of DLBS on the choice of active travel mode in outpatient trips was comparatively analyzed. The DLBS trip data showed that riding distance of most DLBS are less than 6 km. In terms of the age range, the legal age for cycling is 12 years and the age for free bus ticket in Beijing is 60. Therefore, the respondents aged 12 ~ 60 years old with travel distance less than 6 km were selected to study the impact of DLBS on active travel behavior.

Remarkable changes took place in the active travel mode in only a year after DLBS joined the market. As shown in Figure 3 (a) and (b), remarkable changes were observed in the cycling mode (private bike and DLBS). In 2017, DLBS appeared and accounted for 15.9% of the total proportion (9.2% DLBS only and 6.7% DLBS with public transport), which was 3.6 times that of private bike usage (4.4%). The proportion of active transport increased significantly after the advent of DLBS in 2017. This finding is consistent with the related studies (Jia & Fu., 2019). At the same time, there is a severe decline in private bike usage. DLBS obtains a part of private bike users and becomes a replacement. Private bike users have to ride back to their origin, whereas DLBS users can have more flexible choices after their medical treatment. Other travel modes are available for DLBS users to fit their willingness and time demand.

DLBS is properly integrated with public transport service. Among the DLBS usage in outpatient trips (15.9%), the integration of DLBS and public transport travelers (6.7%) account for 42.1% of the total. This finding reveals the importance of DLBS in trips that connect the public transport stations and Beijing Friendship Hospital. In the areas with inadequate public transport resources, DLBS provides a new option for outpatients in their trips to hospitals. DLBS will contribute to solving the first and last mile problem and improve the trip efficiency.



(a) (b)

Figure 3. (a) Active travel mode choice in 2016 and 2017. (b) Proportion of active transport.

Overall, rapid developments in the sharing economy and green transportation have caused the threefold boost in the proportion of cycling mode. The increase in active transport is beneficial to the environment. An improved cycling environment is necessary to meet this trend. Moreover, the rapid development of smartphone will popularize online payments and therefore lead to the promising future of DLBS.

4.2 Trip Experience Evaluation

As discussed above, remarkable changes have occurred in the active travel modes after the introduction of DLBS. The travel mode choice is related to the trip experience. To analyze the subjective feelings of outpatients about various travel modes quantitatively, the respondents were required to score their trip in the punctuality, the convenience, the satisfaction, and the comfort. Table 4 shows that the DLBS indicators are 4.65, 4.77, 4.74, and 4.71. DLBS and walking typically have clear advantages over private bikes. The results are consistent with the changes in travel mode choice in 2016 and 2017.

Compared with walking, riding DLBS saves time and effort. Compared with private bike riders, DLBS users don't have to ride the bike in their return trips. They can use other travel modes in the next trip for other purpose. These advantages make DLBS obtain an 11.71% higher score in the convenience indicator than the total average. DLBS also provide good punctuality of 8.49% higher than the average of all the travel modes, which is valuable for medical appointment.

The evaluation difference of private bikes between registered members and non-registered members of DLBS should be considered. Compared with non-registered members, the registered members of DLBS score 10% higher on punctuality and convenience in private bikes. The findings reveal some shortcomings of the current DLBS. Private bike users who registered in DLBS will feel disappointed if it takes an extra time to search for DLBS bikes. This time delay can affect their subjective feelings on punctuality and convenience indicators.

Table 4.
Evaluation scores of active travel modes.

Mode	Object	Punctuality		Convenience		Satisfaction		Comfort	
		Score	*Deviation (%)*	*Score*	*Deviation (%)*	*Score*	*Deviation (%)*	*Score*	*Deviation (%)*
DLBS	Registered Members	**4.65**	**+8.49**	**4.77**	**+11.71**	**4.74**	+9.22	**4.71**	+11.61
	Non-Registered Members	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Total	**4.65**	+8.49	**4.77**	+11.71	**4.74**	+9.22	**4.71**	+11.61
Private Bike	Registered Members	4.78	+12.74	4.69	+9.83	4.44	+2.30	4.22	0.00
	Non-Registered Members	4.27	+0.71	4.27	+0.00	4.45	+2.53	4.36	+3.32
	Total	4.50	+6.13	4.44	+3.98	4.45	+2.43	4.30	+1.90
Walking	Registered Members	4.73	+11.56	4.76	+11.48	4.79	+10.37	4.64	+9.95
	Non-Registered Members	4.69	+10.61	4.69	+9.84	4.73	+8.99	4.73	+12.09
	Total	4.71	+11.08	4.73	+10.77	4.76	+9.68	4.68	+10.90
Total Average		4.24	N/A	4.27	N/A	4.34	N/A	4.22	N/A

"DLBS": dock-less bike-sharing system; Deviation: "+" means more than the average; "-" means less than the average.

4.3 Travel Mode Alternatives

DLBS has advantages in trip experience due to its. . DLBS provides a new alternative mode for short-distance trips and changes the travel mode choice in active transport. Some travelers gradually shift from other travel modes to DLBS in outpatient trips. Investigating the alternative role of DLBS in multimodal travel is necessary. In the survey, respondents were required to select another mode that they like best to replace the current one. They can also maintain the same mode. The matrix of travel mode transfer can reflect this situation, as shown in Table 5. The columns and rows present the alternative and current modes, respectively. The numbers represent the proportion of this transition. The diagonal numbers reflect the reliance of each travel mode. The data of private bikes and cars are selected from the owners.

From Table 5, active mode travelers have the maximum inclination to use DLBS due to their short travel distance. Travelers who choose walking (29.41%) and private bike users (12.50%) regard DLBS as their favorable substitute. This finding is consistent with those of a related study (Du et al., 2019). 17.24% and 3.45% of current DLBS users select walking and private bike as alternatives. The numbers are significantly less than the proportions of walking and private bike users to choose DLBS. This difference shows the superiority of DLBS. Only one-eighth of private bike riders chose DLBS, which is the lowest among the active travel modes. The significant negative impact of bike ownership on the DLBS choice is consistent with the results of the MNL model in this study.

Table 5.
Matrix of alternative travel mode transfer (%) of registered members of DLBS in 2017.

	Walking	Private Bike	DLBS	Bus	Subway	Private Car	Car-hailing	Taxi	Bus and Subway	DLBS and Public Transport	Other
Walking	26.47	26.47	**29.41**	11.77	2.94	0.00	2.94	0.00	0.00	0.00	0.00
Private Bike	12.50	**12.50**	**12.50**	37.50	12.50	0.00	12.50	0.00	0.00	0.00	0.00
DLBS	**17.24**	**3.45**	**20.69**	20.69	3.45	3.45	17.24	13.79	0.00	0.00	0.00
Bus	1.11	7.78	7.78	24.45	16.67	10.00	13.33	14.44	2.22	0.00	2.22
Subway	1.25	1.25	0.00	30.00	16.25	13.75	22.50	11.25	1.25	0.00	2.50
Private Car	0.00	0.00	5.06	17.72	20.25	22.79	20.25	12.66	1.27	0.00	0.00
Car-hailing	0.00	0.00	**7.89**	31.59	15.79	13.16	21.05	5.26	2.63	0.00	2.63
Taxi	0.00	0.00	**0.00**	25.00	20.83	12.50	8.33	25.00	4.17	0.00	4.17

Bus and Subway	0.00	0.00	0.00	0.00	0.00	13.64	50.00	9.09	27.27	0.00	0.00
DLBS and Public Transport	0.00	0.00	0.00	18.65	0.00	15.39	23.08	0.00	7.69	30.77	4.42
Other	0.00	0.00	0.00	0.00	40.00	40.00	0.00	0.00	0.00	0.00	20.00

"DLBS": dock-less bike-sharing system;
The first column indicates the current travel mode; the first line indicates the alternative travel mode.

More than 30% of "DLBS and Public Transport" and over 20% of DLBS users retain their choices. The findings reveal that DLBS clearly obtain the users' approval. Based on the survey data, the travel distance of "Bus and Subway" travelers is significantly longer than the average. About a quarter of "Bus and Subway" retain their choices whereas half of them prefer car-hailing services.

Although the speed, fare, and trip experience are similar between the car-hailing and taxi, their willingness to choose DLBS is remarkably different. Around 7.89% of car-hailing users consider DLBS a potential alternative but none of the taxi users did. This finding can be attributed to the similarities between DLBS and car-hailing services, such as online smartphone operation. The tendency to shift to DLBS from other modes shows the importance of DLBS in outpatient trips.

Due to the common problems such as lack of parking space, traffic congestion, and inadequate public transport availability, DLBS is sometimes even faster than motor transport in short-distance trips (Faghih-Imani et al., 2017; Levy, Golani, & Ben-Elia, 2017). DLBS is facing an appropriate opportunity for a better development. Meanwhile, the popularity of DLBS can result in remarkable environmental benefits.

4.4 Influence Factors in Daily Trips

To recognize the influence factors of DLBS usage, the answers in the demographic and daily trip sections of registered members of DLBS were collected from the survey in 2017. On the basis of (1), the variables were classified according to the correlations with DLBS choice. The significance levels were divided into 0.1, 0.05, and 0.01. Through the Independence from Irrelevant Alternatives (IIA)test, 21 variables were considered in the MNL model. 13 variables including travel duration, education, online map usage, and heavy rain, were retained due to the significance values of less than 0.1 (bold font in Table 6). The detailed information of variables in MNL Model is listed as Table 1 in the Appendix.

Online payment and map usage are decisive factors in DLBS choice. The popularity of smartphones increases the ease in promoting DLBS. Good cycling condition shows the strong positive influence on DLBS usage. Well-educated travelers have a high propensity for DLBS probably because of their tendency to accept new technology products. Similar to the results from a previous study on DBBS (Sun et al., 2018), weather has evident impacts on DLBS usage. Bike-sharing is seldom selected under severe weather conditions. The model also reveals that DLBS attracts more people who do not own bikes.

The results of the proposed model can be used as strategies of DLBS invention, operation, and management. The government should help DLBS companies to join in the projects and activities to obtain a safe, green, and smart transportation system and improved city life. For DLBS companies, communication technology (e.g., 5G, smartphone, online map, and navigation) will bring additional registered members of DLBS, business opportunities, and benefits. Decreasing the number of DLBS in operation can reduce the maintenance cost. DLBS commercial promotion, such as roadshows, will be valuable in university campuses and science parks of companies during enrollment season. The target users such as freshman students and clerks will learn that they can enjoy convenient cycling by registering for DLBS members. Owing a private bike is unnecessary for them.

Table 6.
MNL model estimation results of the daily trip.

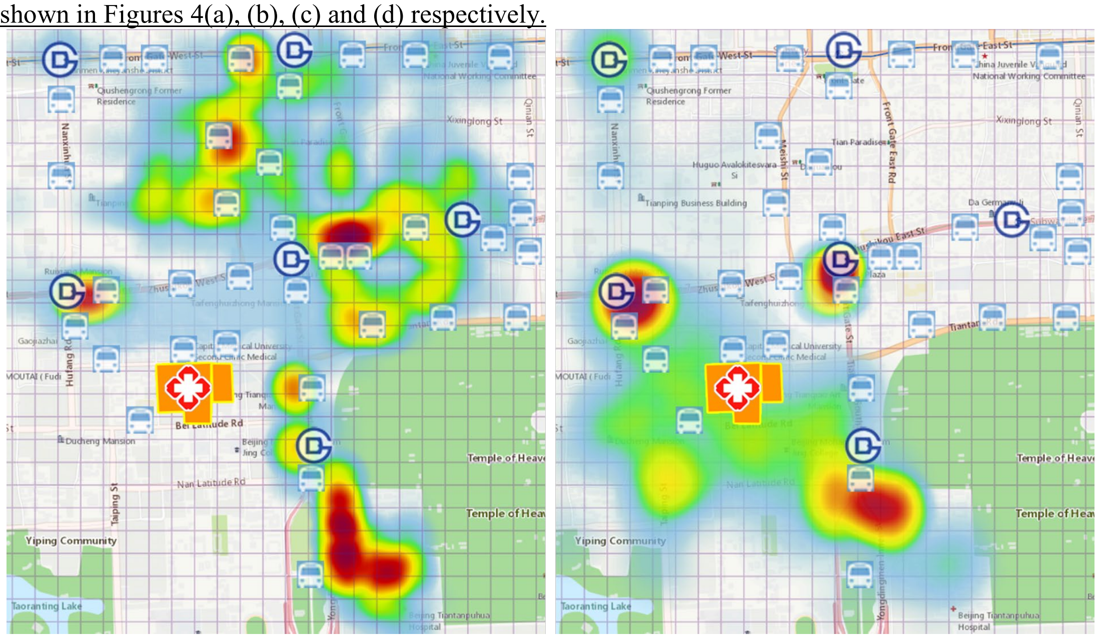
ID	Category	Variables	Description	Sig.	Coef.
1	Basic Information	**Education**	Below Bachelor = 0; Bachelor or above = 1	**0.001*****	**+0.345**
2		**Travel duration**	Continuous	**0.007*****	**-0.130**
3		Age	Continuous	0.201.:	N/A
4		Gender	Male = 0; Female = 1	0.411.:	N/A
5	Job	**Student**	No = 0; Yes = 1	**0.003*****	**+1.524**
6		Clerk	No = 0; Yes = 1	0.018**	+0.655
7		Retiree	No = 0; Yes = 1	0.096*	-0.144
8		Civil servant	No = 0; Yes = 1	0.377.:	N/A
9	Demographics	**Online payment**	Not use = 0; Use = 1	**0.001*****	**+33.946**
10		**Online map usage**	Not use = 0; Use = 1	**0.003*****	**+3.356**
11		Bike ownership	Not have = 0; Have = 1	0.014**	-1.312
		Car ownership	Not have = 0; Have = 1	0.294.:	N/A

12		Minimum acceptable cycling temperature	Continuous	0.095*	-4.432
13		Maximum acceptable cycling temperature	Continuous	0.216.:	N/A
15		Monthly income	Continuous	0.836.:	N/A
16	Weather	**Heavy rain**	No = 0; Yes = 1	**0.008*****	**-1.104**
17		Light rain	No = 0; Yes = 1	0.067*	-0.615
18		Snow	No = 0; Yes = 1	0.328.:	N/A
19		Fog and haze	No = 0; Yes = 1	0.560.:	N/A
20		Strong Wind	No = 0; Yes = 1	0.094*	-0.151
21	Cycling Environment	**Bicycle path with guardrail**	Without guardrail = 0; With guardrail = 1	**0.001*****	**+0.932**

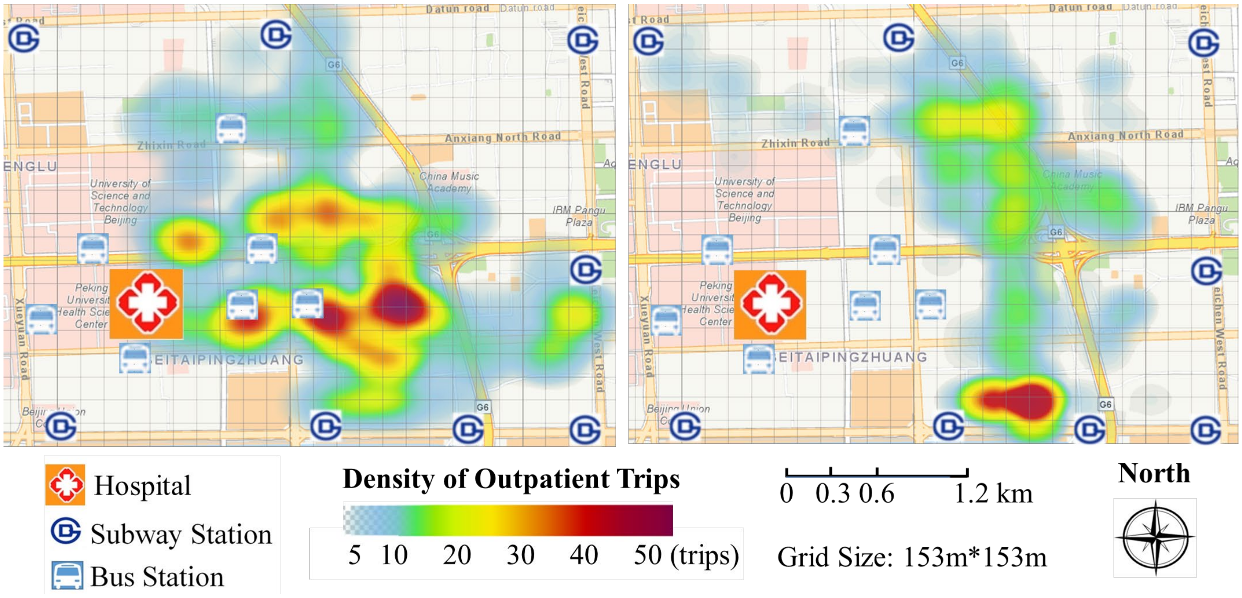
.: means "not significant"; * means "Significant at 0.1"; ** means "Significant at 0.05"; *** means "Significant at 0.01".

4.5 Spatial and Temporal Analysis of Outpatient Trip OD

To understand the OD demand of outpatient trips, further analysis was conducted on the basis of both survey (n_1 = 1,047) and DLBS trip (n_2 = 1,778) datasets. Beijing Friendship Hospital and Peking University Third Hospital were selected as case studies. To discover the spatial characters of outpatient trips, the origins of arrival trips to hospitals and destinations of departure trips from hospitals are shown in Figures 4(a), (b), (c) and (d) respectively.



(a) (b)



(c) (d)

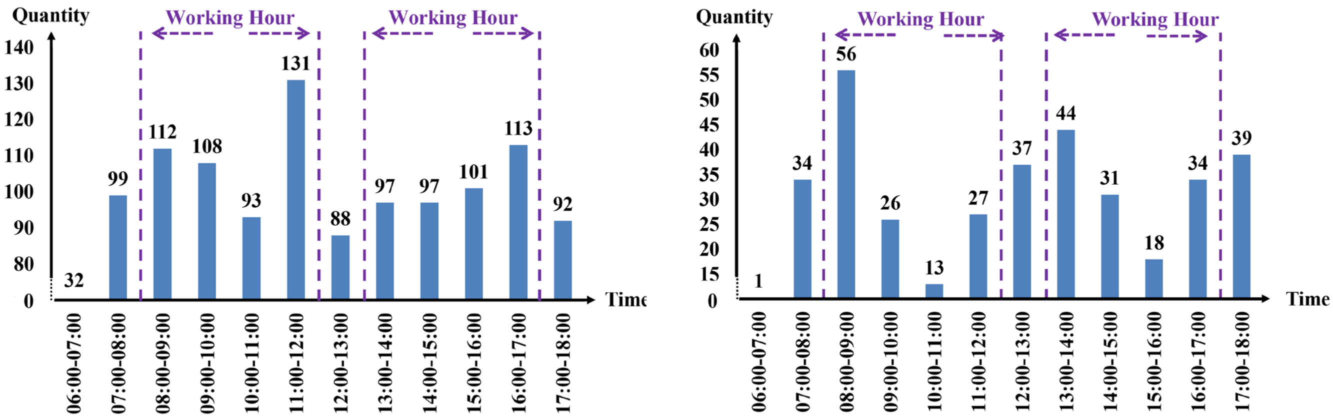
Figure 4. (a) Origins of arrival trips to Beijing Friendship Hospital. (b) Destinations of departure trips from Beijing Friendship Hospital. (c) Origins of arrival trips to Peking University Third Hospital. (d) Destinations of departure trips from Peking University Third Hospital.

A large part of the outpatient trips are generated in public transport stations and residential communities. This visualization proves that around two-fifths of DLBS travelers to Beijing Friendship Hospital are bus and subway passengers. DLBS promotes public transport service in outpatient trips. This finding confirms that DLBS become a feeder of public transport in outpatient trips. Another density area is the residential community located around 2 km from the southeast of Beijing Friendship Hospital. This finding demonstrates the tendency of many outpatients directly going to the hospital from their homes. If public transport service is not convenient enough but the travel distance is short, DLBS can be a popular choice.

By comparing Figures 4 (a) and 4 (b), the destinations of departure trips from Beijing Friendship Hospital are clearly not the same as the origins of arrival trips. The travel purpose of most the leaving outpatients are not returning home. Two of the nearest subway stations are the most centralized destinations, visibly beyond the residential community and bus stations.

According to Figures 4 (c) and 4 (d), Peking University Third Hospital, another highest-level public hospital located in downtown Beijing, also faces the situation of being far away from public transport stations. The two nearest subway stations are 1.3 km and 2.4 km away from. In the arrival trips to Peking University Third Hospital, these public transport stations are important start points for the outpatient trips. When leaving from the hospital, the travel destination is more divergent. The business and residential areas on the east side are the destinations for a large number of DLBS trips. The findings reveal that many outpatients choose DLBS to their workplace and home after the medical treatment. Universities are the main building on the west side of Peking University Third Hospital. As the universities have hospitals on campus, the amount of bike-sharing usage is far lower than those in other areas.

In terms of temporal distribution, the statistic of DLBS usage on workdays of Beijing Friendship Hospital ($n_3 = 1,163$) and Peking University Third Hospital ($n_4 = 360$) are shown in Figure 5 (a) and (b). The high usage of DLBS is generally consistent with the working hours of the hospital. This finding indicates that outpatients tend to arrive before the scheduled time to avoid missing the appointment. The peak usage appears at the beginning and end periods of the morning and afternoon working hours. Going to the hospital at these time periods can reduce the interference to their work and study.



(a) Temporal distribution of outpatient trips to Beijing Friendship Hospital.

(b) Temporal distribution of outpatient trips to Peking University Third Hospital

Figure 5. Temporal distribution of the start time of outpatient trips.

Cosine Similarity is introduced to evaluate the similarity of temporal characteristics of DLBS usage. Cosine similarity can be used to compare the similarity of time series with the same length. The calculation formula is shown in (3).

$$\cos(\theta)=\frac{\sum_{k=1}^{n}\alpha_k \times \beta_k}{\sqrt{\sum_{k=1}^{n}(\alpha_k)^2}\times\sqrt{\sum_{k=1}^{n}(\beta_k)^2}} \tag{3}$$

α_k indicates the number of DLBS usage to Beijing Friendship Hospital during different time periods, k =1,2,3…12;

β_k indicates the number of DLBS usage to Peking University Third Hospital during different time periods, k =1,2,3…12;

$\cos(\theta)$ is the value of cosine similarity between α_k and β_k.

The cosine similarity of DLBS usage between Beijing Friendship Hospital and Peking University Third Hospital is 0.94, which indicates that the temporal characteristics to different hospitals have a strong very similarity.

According to the DLBS trip data, the spatial and temporal characteristics of DLBS usage in specific activities or facilities provide a new research method for investigating the travel behavior. By considering this evidence, DLBS companies can carry out additional reasonable bike assignments and management schemes. DLBS can be further explored using smartphone APPs to meet the demand. Merged with the appointment information, the demand of DLBS usage can be predicted with the mode choice model, which is conducive in solving the allocation optimization problem of DLBS. In addition, DLBS companies can also provide an appointment service for some users who reserve bikes at a certain time slot and area for private demand, such as outpatient trips. This extended application will attract high usage of DLBS.

4.6 Outpatient Trip Classification

Among 1,348 DLBS transactions in outpatient trips in Beijing Friendship Hospital, the relationship of outpatient trip in whole-day activities can be described by matching the user ID. These trips can be divided into four types.

1) Round trips: This kind of DLBS users went to Beijing Friendship Hospital by DLBS. After the duration, they use DLBS (but probably not the same bike) to return to their trip origin. This type had 96 trips in the dataset. These outpatient trips were likely a separate activity in the day.

2) DLBS trip chain: These users also used DLBS both in the trip to the hospital and the trip coming from the hospital. However, they rode to another destination after the medical treatment instead of returning to the origin. A total of 297 trips were recorded in this scenario. This finding is more than twice the first classification. These outpatient trips were a part of the DLBS trip chain in whole-day activities.

3) Arrival trips: There were 514 users chose DLBS only in their arrival trips to the hospital. The next transaction in their DLBS account took place at a location far from the hospital. These riders understandably selected other travel modes in the trips departure for the next travel purpose.

4) Departure trips: The last group of DLBS trips was the departure trips. This group had 441 users. Although DLBS was not their mode of preference in outpatient trips, they unlocked a bike in the DLBS system when they left the hospital.

These four types of DLBS users account for 7.12%, 22.03%, 38.13%, and 32.72% of the total number of travelers. Notably, only less than one-tenth of DLBS travelers consider their outpatient trips as a separate activity. Outpatient trips are typically a part of their whole-day trip chain for multi-activity demands in the majority of outpatients. People will leave the hospital for next activity destination after their medical treatment. Different travel demands in whole-day activities may have various requirements.

The constituent ratio also reveals that over 70% DLBS registered members in outpatient trips used DLBS only in a single trip. Under this condition, good flexibility and convenience of DLBS are crucial in multimodal travel.

5. Discussion

Outpatient trips and worker trips are both essential activities for citizens' daily life. Exploring the characteristics of DLBS usage in different activity trips is helpful for its better development. In urban area of Beijing, the major share of the DLBS trips are commuting trips of workers, taking up about 70%. The ratio of outpatient trips to total DLBS usage is about 3%, which is calculated according to the number of daily outpatient visit and DLBS transactions of hospitals including Beijing Friendship Hospital and Peking University Third Hospital, etc.

The difference between outpatient trips and worker trips are summarized in Table 7. Compared with workers, the outpatients usually have the multi-activity travel demand in a day due to the shorter time duration. The outpatients need more convenient and flexible travel modes to meet their diverse travel demand, and these characters are exactly the advantages of DLBS. Therefore, even though the quantity of worker trips is far more than that of outpatient trips, most of the travelers who ride DLBS to Beijing Friendship Hospital are outpatients, not hospital staffs. The number of DLBS trips to Beijing Friendship Hospital is 1,582, among which 1,348 are outpatient trips (85%) and 234 are worker trips (15%). The factors including parking space and shuttle bus provided for hospital staffs might reduce the possibility of using DLBS in worker trips.

Table 7.
Comparison between the outpatient trips and worker trips

Index	Outpatient trip	Worker trip
Time duration in the hospital	About 1 hour	About 9 hours
Role in all-day trip-chain	A part in the trip chain	Commuting trip
Travel demand of the next trip	Other activities	Home
Return trip	N	Y
Trip frequency	When necessary Less than 3 times in two weeks	Every workday
Arrival time	Anytime during working hours	Before working time
Time duration	Less than 2 hours	Whole working hours
Average travel distance	7.2 km	11.1 km
Parking space	Not enough	Reserved
Shuttle bus	N	Y
Quantity	Little part of daily trips	Major part of daily trips

DLBS can be a new travel trend in response to the increasing challenges in urban traffic. Positive initiatives should be carried out by policy makers and transport providers to improve DLBS services. The proposed system is a potential answer to the first and last mile problem. Compared with private cars, taxis, and online car-hailing, riding DLBS bikes is more affordable and can avoid the issues of traffic congestion and parking space shortage. Meanwhile, DLBS users have faster trips than pedestrians and do not need to return the bike to their origins unlike private bike travelers. Flexibility, convenience, and low cost are the significant advantages of DLBS. These benefits also allow the easy integration of DLBS with public transport. Travelers can use DLBS to connect the public transport stations and their destinations.

6. Conclusion

This paper addresses a pioneer research aims to explore the characteristics of DLBS usage in outpatient trips and its impacts on travelers' mode choice behavior. On the basis of 1,047 survey data in 2016 and 2017 (before and after DLBS joined the market) and the trip big data for 14 days, the characteristics of DLBS usage and its impacts on travelers' mode choice behavior in outpatient trips were jointly analyzed in detail.

This study obtained the following conclusions.

1) DLBS can become a considerable replacement for private bikes and a good feeder for public transport services. The widely used DLBS in outpatient trips to Beijing Friendship Hospital reduces private bike usage by over a third of the total. More than 40% of DLBS usage in outpatient trips connects the public transport stations and hospital.

2) DLBS has satisfactory performance in punctuality at 8.49% higher than the average of active travel modes. The peak hours of DLBS usage in outpatient trips are the beginning and end periods of morning working hours and the end period of afternoon working hour (16:00) due to occupational reasons. Punctuality is a key element in the demand of trips for an appointment.

Compared with other active travel modes, DLBS is a better travel mode with the benefits of convenience and comfort in short-distance trips. Nearly 30% of pedestrians consider DLBS an alternative mode in outpatient trips.

3) The influence factors of DLBS usage in daily trips are obtained using the MNL model. Well-educated travelers or those who can use online payments and maps have the tendency to choose DLBS, especially in good cycling and weather conditions. A system of customer-friendly is important for DLBS users, whose preferences to use smartphone APP are vital in the popularization of DLBS in the market.

4) Outpatient trips are seldom a separate activity but usually part of the trip chain in whole-day activities. Among 1,348 DLBS transactions in outpatient trips to Beijing Friendship Hospital, over 70% travelers ride DLBS only in a single trip while having other activity after leaving the hospital. Hence, DLBS has superiority in travel demand for multiple activities, especially in urban areas with high density.

The research method of combining survey data and trip data should be considered in future studies. Previous studies often use only the survey or trip data but fail to exploit the advantages of both. This study attempts to fill this research gap by using both survey and trip data. The personal attributes of travelers and their views on DLBS modes are analyzed according to the survey data. Whereas the trip data has the advantages of accurate trip attributes in large amounts. Thus, the trip attributes and characteristics of DLBS usage pattern can be obtained. The results from these datasets are compared and verified to improve the research on the impacts of DLBS on travelers' behavior.

DLBS has played an important and positive role in outpatient trips. This phenomenon needs more extensive attention. DLBS is suitable for short-distance activity trips with similar characteristics of outpatient trips, such as appointment-based, short-duration, and multi-activity. The increasing number of smartphone users creates a large DLBS market. Some appointment-based services for DLBS users extend the use of this system. The recent novel autonomous bikes (Pei et al., 2019) may be used to further match the flexible travel demand and meet the specific DLBS requirements in the future. The wide usage of DLBS requires a variety of conditions, such as warm climate and cycling guardrail. At the same time, DLBS may bring negative problems such as irregular parking, sidewalk occupation, bicycle theft, low popularity rate, and maintenance cost. The development of DLBS requires scientific planning and management. The sustainability of urban transportation and environment needs to be considered.

For DLBS companies, the demands near subway stations need to be addressed. In the areas with insufficient public transport supply, DLBS should be distributed to alleviate the low accessibility of public transport and gain wide acceptance. During the epidemic, encouraging travelers to choose DLBS will help to reduce the usage of dense public transport and the risk of infection can get lower. Climate and weather conditions in different cities must also be considered. In cities with hilly terrains, constant rainfall, and low population densities, the promotion of DLBS requires careful consideration. On the other hand, the government need provide sufficient DLBS parking space to avoid encroaching on the space of motor vehicles and pedestrians. By considering urban congestion and energy sustainability issues, the integrated usage of public transport and DLBS should be widely recommended for achieving sustainable and efficient urban transportation systems.

Conflict of interest

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix

The detailed information including sample size and proportion of variables in MNL Model is in Table 1 (Appendix).

Table 1 (Appendix).

Detailed Information of Variables in MNL Model

ID	Category	Variables	Sample Size	Proportion (%)
1	Gender	Male	514	49.09
		Female	533	50.91
2	Age	12 ~ 20	26	2.48
		21 ~ 30	398	38.01
		31 ~ 40	342	32.66
		41 ~ 50	145	13.85
		51 ~ 60	67	6.40
		> 60	69	6.59
3	Education	Junior high school or below	48	4.58
		Senior high school	129	12.32
		Professional college	232	22.16
		Bachelor	459	43.84
		Master or Ph. D	179	17.10
4	Monthly income	< 5,000 yuan	337	32.19
		5,000 yuan ~ 1,0000 yuan	529	50.53
		>10,000 yuan	181	17.29
5	Car ownership	Have	735	70.20
		Not have	312	29.80
6	Bike ownership	Have	478	45.65
		Not have	569	54.35
7	Job	Student	71	6.78
8		Clerk	578	55.21
9		Civil servant	316	30.18
10		Retiree	82	7.83
11	Online payment	Use	752	71.82
		Not use	295	28.18
12	Online map usage	Use	587	56.06
		Not use	460	43.94
13	Travel duration	< 0.5 h	373	35.63
		0.5 h ~ 1 h	289	27.60
		1 h ~ 1.5h	198	18.91
		1.5 h ~ 2 h	119	11.37
		> 2 h	68	6.49
14	Minimum acceptable cycling temperature	< 10 ℃	214	20.44
		11 ℃ ~ 20 ℃	537	51.29
		21 ℃ ~ 35 ℃	296	28.27
15	Maximum acceptable cycling temperature	< 10 ℃	0	0.00
		11 ℃ ~ 20 ℃	109	10.41
		21 ℃ ~ 35 ℃	214	20.44
16	Weather	Heavy rain	0.00	0.00
17		Light rain	1.43	1.43
18		Snow	6.97	6.97
19		Fog and haze	4.20	4.20
20		Strong wind	2.01	2.01
21	Cycling Environment	Bicycle path with guardrail	12.03	12.03
		Bicycle path without guardrail	32.95	32.95
		Not ride	55.01	55.01