What is the best catchment area of bike share station? A study based on Divvy system in Chicago, USA

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***Abstract*—Bike-sharing systems are becoming more and more popular both in the United States and around the world due to their easy accessibility and environmental friendliness. At the end of 2016, more than 430 bike-sharing programs and nearly 2.3 million bikes were available to the public around the world. In the United States, 123 million trips have been made using shared bikes since 2010. In 2017, the number of trips made using shared bikes has reached 35 million, which is 25% higher than that of 2016. As an increasingly popular mode of transportation, bike-sharing systems are designed for short-distance trips, which not only improves the efficiency of short-distance travels but also alleviates traffic congestion and air pollution. In addition, interests in bike-sharing systems have been fueled by several cities, including Washington DC, where bike share has quickly become a convenient and popular transportation option. Feasibility is the first to study for parties considering implementing a bike-sharing system, detailed information such as the location of stations, number of shared bikes and especially the appropriate size of catchment area should be estimated precisely by system planners. Afterwards, with such information reasonable policies can be made to ensure the operational efficiency of system and maximize system-wide ridership. However, little information is available on what size of an appropriate catchment area should be used. Due to its simplicity in application, direct demand model is gaining more attention in demand forecasting. In this study, direct demand models were used to explore the best catchment area of the bike-sharing stations in Chicago, USA. In order to find out the best catchment area, multiple radii distance range from 200 m to 800 m were established around stations in the system. Results indicated that model fitting results do not vary among different catchment areas. Thus, for purpose of completing their studies, whatever catchment area is readily available or calculated can be used by direct demand modelers. And more attention should be paid by researchers to explore the appropriate boundaries in the future.**

Keywords—bike-sharing system, catchment area, direct demand model, divvy

I. INTRODUCTION

Over the past decade, bike-sharing systems as an nonmotorized mode of transportation have been expanded in number and popularity both in the United States and around the world. For providing short-distance service to users, bike-sharing systems allow users to pick up or drop off a shared bike at any stations in the city the system is served. The systems also offer a cash payment membership option for users who need to use a shared bike. By the end of 2017, about 120 bike-sharing systems are either operational or in the planning phase since Washington DC, the first major city in the United States to start a new-generation bike-sharing system in 2008. In addition, according to some preliminary statistics, 35 million trips have been made using shared bikes in 2017 in US, the trips number has increased by 25% compared to 2016 [1]. At present, interests in bike share have been fueled by success in several cities, including Washington DC, Toronto and Brisbane, where bike share has quickly become a new popular and convenient urban transportation option.

Due to its easy accessibility and environmental friendliness, bike-sharing systems are playing a more important role in transportation. This is because it can not only improve the efficiency of short-distance travels but also make contributions to alleviate traffic congestion and air

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pollution. Feasibility is the first to study for parties considering implementing a bike-sharing system. In addition, to provide a higher quality services for users, information such as the number of shared bikes, location of stations and especially the size of the service area, should be deeply studied by system planners. Afterwards, it can be of benefit to system planners who are designing or modifying systems with the goal of maximizing system-wide ridership and applicability based on a fully understanding of a bike-sharing system.

Catchment area is defined as the vicinity of bike share stations in which users in the area desire to use bike-sharing system can walk a distance to the nearest station comfortably. It plays a vital role in the planning of bike-sharing systems. Although multiple sizes of catchment area were accepted by previous studies, there is no uniform standard in the academic filed regarding what size of catchment area should be used. Therefore, the motivation of this paper is to fill this gap of research. We analyzed Divvy, the bike-sharing system in Chicago with the focus on determination of catchment area in the system. According to some studies, socio-economic, built-environment and transit-related factors show a strong correlation with travel demand [2-4]. Thus, in our analysis, direct demand models are employed to explore the effects of socio-economic attributes, built-environment factors and transit-related factors on bike share ridership at station level in multiple vicinities of stations.

The remaining of the paper is organized as follows. The second section gives a detailed review about previous studies. The third section demonstrates data handling and methodology. And the fourth section explains the analysis and findings. Conclusions are outlined at the end.

II. Literature Review

In previous research, there is no information available on how far users will travel to get a shared bike. Range of various sizes of catchment area based on different methods had been set around stations by researchers in their studies.

The distance between stations in bike-sharing systems, as well as the unique urban forms of cities are often considered to define an appropriate catchment area. Multiple sizes of buffer areas were adopted for different research purposes: 1) a 300-m buffer around each station in Chicago's Divvy system was established to study users' destination choice preferences, 2) to explore the impact of land use attributes and urban form on bike flows, for example, in BIXI bike-sharing system of Montreal, a 250-m buffer was found and created to be an appropriate walking distance. 3) and to investigate the influences on station's demand considering the spatial and temporal interaction, for example, a radius of 250-m around stations in New York Citi Bike system was employed [5-7]. In their studies, attributes such as stations with higher capacity or longer bike paths nearby play an important role in increasing bike share ridership. In addition, points of interest including parks, restaurants also influence users' choice. Furthermore, the distance between stations to CBD (Central Business District) shows a negative relationship to ridership that the farther the distance from stations to CBD, the fewer the usage of the stations. Similarly, for the trip length, the longer the trips, the lower the likelihood of choosing a station as destination. Job density as well as population density also affects utilization of bike-sharing systems.

"As-the-crow-flies-distance" is an idiom for the most direct path between two points [8]. Both in the system planning stage and system expansion stage, DDOT (District Department of Transportation) has adopted this distance to examine the attributes of transportation sites. Apart from this, some researchers used a crow's flight radius of 0.5 miles (804 meters) to create the buffer as well [9]. In order to analyze attributes affecting bike share utilization, a half-mile buffer surround each station was established in Washington DC's Capital Bikeshare system. And analysis results indicate that stations in bike-sharing system located near bike lanes would increase ridership. Moreover, population density also contributes to increase the usage of bike-sharing system. Another exception is that the number of households without access to automobile, where it was assumed that a positive relationship would be shown, but it was negatively related to bike share ridership.

Furthermore, as the users desire to walk to their nearest bike stations, an assumption is introduced, that a-quarter-mile network distance defined by Thiessen polygons, was considered as a reasonable estimate for the farthest distance a user would walk to obtain a bike [10]. Analysis results show that bike share stations which were placed around busy metro stations or bike infrastructure tend to have a high bike share usage. In addition, the number of docks as well as bike racks near bike share stations also increase bike share demand of system.

In addition, based on the theoretical minimum of walkable catchment, in order to analyze the effects of natural and built environment attributes on the usage of shared bikes, a 400 m radius, which is equivalent to a five-minute walking distance, was used by some researchers to create circles centered on Brisbane's CityCycle stations [11]. According to the results, off-road bikeways near stations contribute relatively positive to the utilization of bike-sharing system. Moreover, stations with nearby recreational facilities attract people to use shared bikes.

The size of catchment area considering practical experience by previous researchers often provides a starting point for later researchers. Thus, many following researchers, in their studies, used a definite radius distance of catchment area that the former researchers had conducted [12-14]. In order to forecast bike share ridership, demographic features and built environment attributes were all calculated based on a half-mile buffer in four U.S. bike-sharing systems. And as the results indicate, that station network including network density, distribution and size are all significantly correlated with bike share ridership, as well as the majority variables tested in analysis; For the same purpose, a 400-m buffer was employed by other scholars to predict bike share ridership in three U.S. bike-sharing systems. The results demonstrate that a number of variables including population density, income level, existence of bikeways and proximity to a number of other bike share stations have a closely positive relationship to bike share ridership; In particular, Nice Ride, the bike-sharing system in the Minneapolis–St. Paul Metropolitan Area, researchers adopted another 400-m walking distance buffer setting around bike share stations to identify correlates of bike activity for Nice Ride. Each explanatory variable has a significant correlation with the number of bike share trips. Moreover, neighborhood socio-demographics, proximity to the central business district, and distance to other stations in

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their analysis are all closely associated with the number of bike share trips.

Although much work had been conducted by scholars using many approaches to examine determinants of bike share ridership at station level as well as trip level, there are still several dimensions remained to be investigated. As it is also evident from previous studies, researchers tend to focus on adopting a definite straight line distance or radius distance centering bike share stations in their studies, but little attention is paid to find out an appropriate catchment area We believe that this is the first of its kind research to explore the best catchment area around stations in bike-sharing system using a direct demand model.

III. Data and Methodology

Variables tested in analysis are defined in this section. The process to compile the regression model dataset and descriptive statistics of data are presented as follows. Two sets of dataset including trip dataset provided by Motivate, operator of Divvy system, and Smart Location Database (SLD) provided by the United States Environment Protection Agency are used to explore the best catchments.

A. Data

In the Divvy bike-sharing system, since it provides a number of shared bikes for users, the system has quickly become an important transportation option across Chicago. Trip data of Divvy system can be downloaded from the official website. Moreover, every trip record contains detailed information including the time, latitude and longitude of start (end) station, user attributes (age and gender only for subscribers). In particular, the trip dataset disaggregates usage by user type, subscribers refer to those users who pay an annual/monthly subscription fee to use the shared bikes while customers do not. In this study, little differences were observed between the trip analysis of July and monthly average in the second half of 2014. Therefore, we selected a month of data – July, to represent the usage of shared bikes in Divvy. Table 1 shows the descriptive statistics of total bike share rentals from 300 stations in July (300 bike share stations in operation were analyzed in our study), and a map of the trips generated at bike share stations in July 2014 is presented in Fig. 1, the total rentals from stations ranging from 19 to 11149. Based on the rentals, the data are broken down into quartiles. Moreover, as shown in the map, in areas close to the center of city, especially in the CBD (central business district) area, trip generation rates are the highest, and the rates are relatively lower in areas far away from the city center as assumed that more bikes would be used in area close to CBD due to a high level economic activities.

The Smart Location Database (SLD) summarizes several demographic, employment, and built environment variables at the Census Block Group (CBG) level for all 50 states in US. Variables quoted the data of Chicago city in SLD were used as input to the travel demand models.

A variety of socioeconomic characteristics are considered in our research. Residential population and housing units near stations, as thought to encourage the usage of bikes are considered, as well as the work population variable. In addition, as a commuter mode of transportation, people living near bike stations may choose a bike to go to work, thus the quantity of employees near stations is investigated. Moreover, to assess whether the family income level may affect the bike share ridership, the proportion of people based on home-location earn $1250 or less per month, greater than $1250 but less than $3333 per month are separately calculated.

TABLE I. Descriptive Statistics of The Total Rentals in July

Min	Mean	Median	Max	Std
19	1368	961	11149	1376

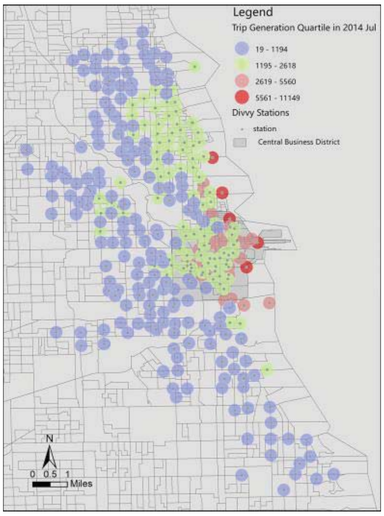

Fig. 1. Quartiles of trip generation for bike share stations in July

TABLE II. Definitions for All Variables Used in The Study

Variables	Definitions
Dependent	
Monthly rentals (log-transformed)	The total number of bike rentals at stations in Divvy in July 2014
Independent	
Socio-economic variables	
Population	Population size
Employment	Total number of jobs
Employee	Total number of employees
P_wrkage	Percentage of population that is employed with age over 17
Household	Number of housing units
P_owncar0	Percentage of zero-car housing units
LowwageL	Percentage of employees earning 1250/Month or less living in CBG
LowwageW	Percentage of employees earning 1250/Month or less working in CBG
Built-environment variables	
NetworkDens	The road network density
IntersectDens	The street intersection density
Dis_stop	Distance from population weighted centroid to the nearest transit stop (in meters)
Dis_CBD	Distance between bike share stations to CBD area
Transit-related variables	

Capacity	Number of docks at bike share stations
Bikestanum	Number of neighboring bike share stations in the buffer areas
Metrostanum	Number of metro stations in the buffer areas
Busstanum	Number of bus stops in the buffer areas
Lenbikeway	Total length of bikeway in the buffer areas

The total employment variable is also considered in this research, as we think that may increase the utilization of the bike-sharing system. Further on, the proportion of employees based on work-place earn $1250 or less per month, greater than $1250 but less than $3333 per month are also considered to test their influence on bike share usage.

Regions with higher density of roadways indicate a higher accessibility index. People in such areas can be easier to choose a suitable transportation mode to get to their destinations. Thus, characteristics like road density and intersection density are employed in the study to examine the effects on bike share ridership. In particular, minimum walking distance between the population weighted Census Block Group (CBG) centroid and the nearest transit stop is summarized in the Smart Location Database (SLD), and the distance is also investigated for its impact on bike share usage.

Considering that the setting of bike lanes or routes in the urban transportation system can affect users' willingness to travel by shared bikes. In this study factors such as bikeway or bike routes are used to measure whether the existence of transportation facilities attracts more users to use bike-sharing system. This data was obtained from open-sourced websites from the local jurisdictions, the total length of bike lanes or bike routes within multiple size buffer area vicinities were then calculated in the Divvy bike-sharing system. In addition, the number of neighboring bike share stations (excluding the destination station) were computed in multiple buffers for purpose of capturing the influence of neighboring stations.

The variables mentioned above were then associated with each station across Divvy bike-sharing system using ARCGIS software. In this study, multiple sizes of buffer area, radii of 200 m, 300 m, 400 m, 500 m, 600 m, 700 m and 800 m were separately created around stations across the Divvy bike-sharing system. The 800m distance was used as the farthest distance in the previous studies, thus we chose the 800m as the maximum distance setting around stations in the current study. Census block group files were linked to station buffer areas separately, a GIS function called "intersect" was employed to measure the proportion of every block group's area falling within every buffer area as the shapes of the station buffer areas do not exactly match the census block group shape. The intersect areas intersected by buffer areas and census block groups area were then used to calculate the weight to the block group, all the intersect areas (lying entirely or partially within the buffer area) in a finite station buffer were combined to obtain data linked to each census block group's data. The resulting data for stations buffer area is a weighted average of census block group data.

Table 2 presents definitions for all variables considered in our analysis.

B. Methodology

To determine a suitable catchment area, several direct demand models were used to estimate station-level ridership in Divvy bike-sharing system. According to Cevero, using direct demand models, essentially a statistical regression based on observed ridership, is a simple alternative to full-blown travel models to predict transit ridership on transit stations, corridors and systems [15]. For the advantage of direct demand model in transit planning field, the pedestrian scale dynamics play a critical role in determining transit ridership which are hardly shown up in regional travel models. However, direct demand models can reflect the actual land use characteristics in these areas that are mostly dominant in determining transit ridership by focusing an area defined with stations (They are also the areas where land use is most likely to be influenced by transit). Therefore, direct demand models were employed in our study to estimate the relationship between bike share stations surrounding characteristics and bike share station-level ridership followed by determining if there would be a suitable catchment area that these stations served.

In direct demand models, the total rentals at station level were considered as dependent variable (n=300), then a natural logarithm transformation was applied to bike rentals to obtain a closer resemblance with normal distribution due to the distribution of rentals showing a highly skewed plot. In addition, stepwise regression models were used to eliminate multicollinearity between variables. The others variables including socio economic attributes, built-environment factors and transit-related factors, were used as input in direct demand models in this study.

IV. Analisis and Findings

The result for Divvy bike-sharing system by service boundaries is shown in Table 3.

To identify the type of catchment area that is most influential for estimating bike share ridership at station level, Akaike's information criterions (AICs) and determinant coefficients (R-squared) were analyzed in our models. For the analysis of models, a well-fitted model tends to yield a higher R-squared value or a lower AIC value. But different from what we expected, the AICs statistics did not show a significance difference between service boundaries, and the R-squared values also change weakly among different catchment areas in the analysis of the Divvy bike-sharing system.

Analyses of variables in our study revealed that most variables play a key role in affecting bike share ridership at station level, although the minority group of variables did not show a significant or consistent results in the bike-sharing system. In analysis of the system, counterintuitively, the population variable in different catchment sizes did not show a significant correlation to bike share ridership. And the number of employees showed little influence on bike share ridership except in the 700 m and 800 m models which positively affect utilization of bikes. In addition, in multiple sizes of catchment area, employment variable was positively significant for 400 m to 800 m models. Analyses of proportion of working-age population indicated that in a catchment with a higher proportion, it tends to have more usage of bikes in the system, and the proportion size was positively correlated to bike share ridership up to 800 m

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radius. We in particular found that household size in our analysis had a negative association with bike share ridership from 500 m to 800 m models. As previously assumed, households without access to a vehicle may tend to use bikes frequently, the 400 m to 800 m models showed a positive relationship between the car-zero households with ridership. Moreover, for the proportion of low-wage income population who live or work in the catchment area, regardless of different service boundaries, it explained two distinct relationship to bike share ridership in Divvy: for the low-wage people who living in the catchment area, a statistically significant and negative association was shown with ridership across models. But for low-wage people who working in the catchment area, it showed a strong positive effect on bike share ridership. In other words, low-wage people who work in the catchment area are more likely to use shared bikes than those who live here.

TABLE III. ANALYSIS RESULTS FOR DIVVY BY SERVICE BOUNDARIES

	200m		**300m**		**400m**		**500m**		**600m**		**700m**		**800m**	
	Coef.	***t***	***Coef.***	***t***	***Coef.***	***t***	***Coef.***	***t***	***Coef.***	***t***	***Coef.***	***t***	***Coef.***	***t***
Intercept	2041	3.435	1677	2.692	1512	2.222	1996	2.738	1573	2.001	1895	2.309	2110	2.464
Socio-economic variables														
Population							0.058	1.591	0.065	2.267				
Employment					0.004	2.129	0.002	1.701	0.004	3.044	0.004	3.900	0.005	4.648
Employee											0.125	2.976	0.127	3.585
P_wrkage	5606	9.548	5962	9.695	6186	9.042	5597	7.575	6319	7.798	5946	7.032	5820	6.651
Household							-0.083	-1.494	-0.090	-2.026	-0.055	-2.060	-0.068	-2.927
P_owncar0					423.5	1.407	841.2	2.409	703.7	1.863	867.0	2.065	1079	2.420
LowwageL	-5539	-7.264	-5372	-6.839	-5826	-6.674	-6457	-6.594	-6717	-6.223	-5825	-5.273	-6374	-5.506
LowwageW	978.1	3.271	1341	4.181	1673	4.792	2077	5.674	2217	5.841	2202	5.426	2256	5.081
Built-environment variables														
NetworkDens	5.008	2.538	5.396	3.330	4.316	3.912	3.773	3.664	2.046	1.985				
IntersectDens									0.160	1.607	0.248	3.877	0.223	4.127
Dis_stop			-0.546	-2.047	-0.481	-2.852	-0.500	-3.953	-0.377	-3.777	-0.330	-3.934	-0.284	-4.149
Dis_CBD	-0.047	-3.506	-0.039	-2.723	-0.038	-2.594	-0.027	-1.895	-0.029	-1.797	-0.033	-1.981	-0.030	-1.831
Transit-related variables														
Capacity	39.29	5.194	37.30	5.149	36.81	4.956	31.63	4.451	29.84	4.242	28.97	4.162	28.27	4.109
Bikestanum					-76.98	-2.714			-37.56	-1.841	-53.95	-3.151	-59.55	-3.850
Metrostanum													-27.26	-1.448
Busstanum	-18.36	-1.616	-15.15	-2.209	-17.22	-3.298	-17.15	-4.053	-11.90	-3.600	-9.677	-3.336	-6.802	-2.638
Lenbikeway	0.182	1.850	0.089	1.536	0.065	1.573	0.047	1.468						
Modal statistics														
R-squared	0.702		0.728		0.754		0.770		0.783		0.790		0.798	
AICs	-382.3		-406.7		-431.2		-454.0		-470.0		-480.3		-490.3	

Note: All the coefficients in this table were taken to a 1000-fold increase.

Among the built-environment variables, they showed different effects on bike share ridership. In analysis of the effect of road network density on bike share ridership, a statistically positive relationship with bike share usage was showed from 200 m to 600 m models. Same for the intersection density which was positively related to ridership from 600 m to 800 m models. In particular, the distance from bike share stations to CBD were significant for all radius models. For the distance increased by one meter from stations to CBD area, the bike share ridership would be reduced by 1.048 based on the 200-m model. Furthermore, we also found that distance from population weighted centroid to the nearest transit stop showed a significantly negative relationship to bike share ridership except the 200-m model. These findings indicate that the urban network form plays a vital important role in promoting bike share usage. It is more important to point out that the farther the distance from a station to CBD area, the less frequently shared bikes would be used. Likewise, the distance between population weighted centroids to their nearest transit stop may reduce the bike share usage demand.

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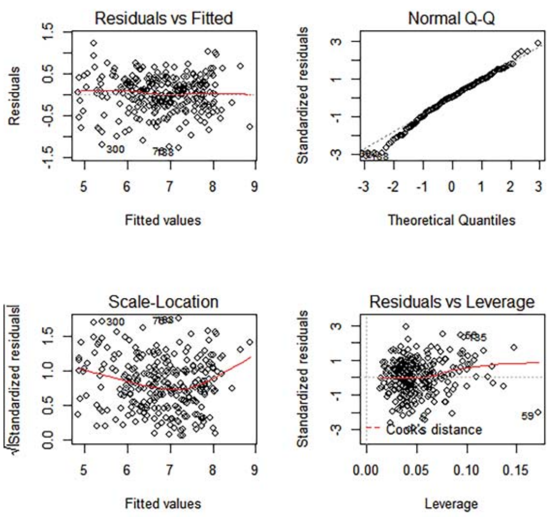

Fig. 2. The 800-m model diagnosis diagram

For transit-related variables, capacity showed a statistically significant and positive relationship to bike share ridership across all models. For stations' capacity increased by one dock, bike share ridership would be increased by 1.040 based on the 200-m model. In addition, neighboring bike share stations in this study had a negatively relationship to bike share ridership for the 400 m, 600 m, 700 m and 800 m models. The number of metro stations in vicinities showed weakly influence on bike share usage. And the number of bus stops in a catchment area, regardless of different service boundaries, was negatively associated with bike share ridership. In addition, the length of bikeway showed a statistically significant and positive relationship with bike share ridership across all radius models. These findings indicate that extending the length of bikeways and capacity of stations may increase bike share usage demand.

In addition to the above analysis, the model diagnosis diagram which is drawn according to the 800-m model shows the largest R-squared value among multiple models. As can be seen in Fig. 2, it is feasible to employ stepwise regression method to model the factors affect the station level ridership based on multiple sizes of buffer area.

V. CONCLUSIONS

Although many cities around the world have implemented bike-sharing systems, little information is available on how far users in a bike-sharing system would be willing to walk to use the system. In this study, we explored the relationship between bike share ridership and bike share station's catchment area in Chicago's Divvy bike-sharing system. Based on different distance radii of catchment areas, multiple models were analyzed across the Divvy bike-sharing system. Model results showed that walkable distance that range from 200 m to 800 m, the proportion of working-age population and households without access to vehicles played an important role in promoting bike share ridership. In addition, results indicated that the changes of catchment area had no consistent relationships with bike share ridership. according to the models fitting results, the R-squared value changed from 0.702 to 0.798. As we assumed that the best catchment area of bike share stations would be accompanied by a higher R-squared value when fitting a model, the model fitting results revealed that as the buffer range increases from radius of 200 m to 800 m, the R-squared value of models increase accordingly. Furthermore, a 0.5-mile meters radius of catchment area were often applied by scholars to investigate characteristics of transit station, a smaller range of bike share station catchment would tend to be suitable. In other words, our model fitting results do not vary among multiple different catchment area, which are consistent with conclusion drawn by Cevero that little was gained from using a particular station catchment area or type over another for the purposes of predicting ridership to verify whether the half-mile can represent the best transit station catchments [15]. Furthermore, it also a sign that whatever the catchment area was easily calculated or available for the direct demand modelers as well as bike share system planners who would like to optimize the system was appropriate to carry out their duties. Overall, our findings confirm that for a catchment area where bike share stations can provide service for users within the area was far from clear. More attention should be paid by researchers to explore the appropriate boundaries in the future.

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