Life duration of bike sharing systems

Jie Zhang[1], Meng Meng[2*], Puay Ping Koh[3], Yiik Diew Wong[4]

1. Department of Engineering, University of Cambridge, Cambridge, CB3 0FS, UK
2. School of Management, University of Bath, Bath, BA2 7AY, UK
3. Land Transport Authority, Singapore 575701, Singapore
4. School of Civil and Environmental Engineering, Nanyang Technological University, Singapore 639798, Singapore

[*]Corresponding author: Email: mm3042@bath.ac.uk

Abstract

Many factors have been advanced to predicate the sustainability of bike sharing system (BSS) and bike sharing usage, such as fleet size, number of docking stations, payment type and financial support, but there have been few studies that examine survival duration of BSS' operation. Therefore, this study investigates the determinants of BSS' duration, using bike sharing monitoring map and respective annual report data from 106 cities around the world. Three categories of independent variables, namely infrastructural factors, social factors and economic factors are included in the generalised linear model (GLM). The findings indicate that coverage area, system capacity and payment type will affect the sustainability of bike sharing operation. Moreover, financial support and purchasing power parity (PPP) per capital are the distinctive factors that seem to influence the likelihood of success of a BSS. Payment method affects the survivability of a BSS after the system is stable.

Key words: bike sharing; influence factors; infrastructure; generalised linear model

1 Introduction

Bike sharing system (BSS) has been flourishing in the face of the COVID-19 pandemic as people try to avoid the usage of public transport. It is essentially a mobility strategy that entails sharing the use of a bike fleet (Zhang et al., 2020). A BSS offers an alternative public transport, encourages more cycling, improves a city's image, provides complementary service linking transit stations, reduces congestion and increases accessibility. Bike sharing has gone through an evolution from first-generation to the present fourth generation (Zhang et al., 2019). The first generation uses a fleet of bikes, usually recovered from abandonment and painted the same colour, which is fixed up and distributed throughout an area and being available for free use. The second generation involves a locking system with coin access at dedicated locking location, which is aimed at correcting for the problems of disorganisation and theft experienced by first generation schemes. The third generation is a popular scheme of first 30 minutes of free bike use yet harnesses "smart card" technology in order to make the bike sharing even more efficient. The fourth generation realises real time tracking of bike, which enables users to check on their cell phones regarding when and where the specially designated bikes are available (Zhang and Meng, 2019).

Many major innovations in the history of bike sharing occurred in Europe, but today BSS exists in all six continents. At present, there are an estimated 357 active BSSs in 52 countries around the world with over 361,000 bikes (O'Brien, 2020). BSS differs from city to city, in terms of size and manner of operation, with adaption to local needs of each city. The Canada bike sharing guide (Transport Canada, 2009) has suggested a series of shortlisting criteria for a BSS to work. These include a large system size (catering to at least 200,000 people), high population/employment density, good cycling infrastructure provision, inter-modality potential, a relatively flat terrain, good climate and a high existing level of bike use. The bike share planning guide in New York compiled five elements that would make bike sharing work (ITDP, 2018). They are station density, bikes per resident, coverage area, quality bikes and easy-to-use stations. A quality BSS needs 10-16 stations per square kilometre, an average spacing of about 300m between stations, 10-30 bikes per 1,000 residents, at least 10 km^2 coverage area, durable and practical bikes and an easy-to-use bike checking out system. Other factors contributing to successful bike sharing include density of employment, education and activities, pricing, access, operating hours, marketing, cycling infrastructure and regulation of vehicles, car ownership level, demography of population, cycling culture, public transport supply, climate and topography.

Apart from the general planning guide, scholars also started to investigate the factors that may affect the successful operation of a BSS (Fishman et al., 2015; Matthson and Godavarthy, 2017; Si et al., 2019; de Chardon, 2019; Ji et al., 2020). de Chardon et al. (2017) examined the usage from 75 systems and found that system expansions do not increase system performance, and cycling infrastructure is related to BSS performance. Sun et al. (2018) investigated the unsuccessful experience of the Pronto programme and found that effects of hilly terrain and the rainy weather were two commonly perceived contributors to the failure. Shi et al. (2018) discussed the factors that were critical to dockless BSS sustainability from a stakeholder-oriented network perspective. Li and Kamargianni (2018) inspected the factors affecting mode choice behaviour with a focus on bike sharing and explored the effectiveness of different policy options aiming at increasing bike sharing ridership. Yuan et al. (2019) proposed a unified mixed integer linear programming model for optimal bike sharing system planning from an integrated and long-term perspective. More review can be found in Ricci (2015), Audikana et al. (2017) and Chen and Zhu (2020).

The above studies discussed either the experiences from successful systems or lessons from failed systems. Documentation on how to attain sustainable bike sharing has not kept pace with the proliferation of BSS. With the recent attention on sustainable development, bike sharing stands out as a highly desirable transportation policy that can be implemented quickly. In order to promote the usage of bike sharing, it is expedient to establish the relationship between various influence factors and local situation. Existing BSSs have accumulated valuable data on their operations which provide experiential information useful for planning and design of future BSSs. This paper evaluates the experiences from past and current bike sharing schemes around the world, excluding bike rental systems which require users to return bikes to origins. In particular, the influence factors that affect the duration of a BSS in operation cover the initial launch period as well as longer-term's operation as investigated based on data from 106 systems using generalised linear model (GLM).

The rest of the paper is organised as follows: typical failure cases and current BSS operation situation are described in Section 2. Section 3 develops the generalised linear model to analyse the relationship between the duration of BSS and various influence factors. Section 4 provides the conclusion of this study.

2 Typical cases

2.1 Failure cases

Many BSSs have been introduced but not all have survived. Notwithstanding economic reasons, there could be many other factors contributing to the failure, such as theft/vandalism, politics and mismanagement, geographical constraint or simply lack of interest. The world's first known bike sharing system, the White Bicycle that was launched in the 1960's in the Netherlands, failed due to theft and vandalism (Schwartz, 2009). In Paris, 80% of the bikes in Paris' Vélib bike-share system were damaged or stolen in 2012. The Paris City Hall official responsible for monitoring the scheme reckoned that thefts and repairs cost €1 million in 2012 (O'Sullivan, 2013). As many as 56 of the 100 bikes were stolen during the first 15 days in Rio de Janeiro's first BSS in 2009. This system was re-launched in 2011 after improving the security system and no bike was stolen in the first month into the new system (Moraes, 2011). Toronto bike share system did not survive due to lack of funding, which ran from 2001 to 2006 and ceased to exist after it was unable to secure enough funding to continue its operations (Schwartz, 2009). The Smartbike DC system that was launched for the District of Columbia in USA in 2008 also failed two years later. The reasons for its failure included poor promotion of the system, only long-term memberships were sold and a very small scale of only 10 stations which limited its utility (DePillis, 2010). Several studies have shown that the major failure of Australian BSSs (Brisbane's CitiCycle and Melbourne Bike Share) is the helmet laws. The average usage rate per bike was less than 1 hire a day (Alan, 2014). Australia is by far the only bike sharing scheme that mandates and enforces helmets. Roma-n-bike system was introduced in 2008. Roma sits on its famous seven hills, where the residents are unwilling to abandon cars and scooters. The system failed in 2014 when it was almost impossible to find a bike in Rome (Migliaccio, 2014). Singapore's first bike sharing scheme Town Bike supported by NTUC (The National Trades Union Congress) Income lasted 4 years and failed in 2008 due to insufficient bike infrastructure (The Straits Times, 2011).

The fourth generation of BSS has not always been successful. Ofo, one of the biggest bike sharing system platforms in the world during 2016-2018, faced bankruptcy and had withdrawn from most countries (e.g. US, Singapore, UK) since December 2018. The reasons behind the failure are complex. But some major issues have been identified. Ofo ran out of capital and faced heavy competition from competitors. Meanwhile, Ofo over-expanded the business to global before dominating the domestic market, which took time and money to reduce the competition locally. Ofo did not improve its business ecosystem so that it could no longer have the economic power to compete as well. It is clear that bike sharing is going to be part of a more comprehensive mobility and payment services. Those points weaken the competitive power of non-integrated operators in China and overseas.

2.2 Current BSSs at 2020

The reasons for the failure of BSSs vary, but often, incomplete plan and design according to local content are to blame. Nevertheless, there are many successful cases that are still in operation up to now. The success rate of a BSS is typically measured using two metrics namely the average number of daily uses per public bike and the average daily bike trips per resident. New York's BSS (Citi Bike) registered an average of 8,105 bike trips per day and 25,276 year-subscription members in the first five days. Each bike is being used 4-6 times per day. In Hangzhou which has the largest BSS in China, bike trips account for 43% of all trips, and the city's BSS is partly to credit for the high bike usage. China has the largest dockless bike sharing market, which has been dominated by three major players. The brutal growth phase of the sharing economy industry is over. The competition has gradually slowed, various bike sharing companies have raised prices and their profit model has shown a substantial improvement. As of the COVID-19 pandemic, bike sharing is in a recovery growth as bike is considered as one of most safe modes to commute. The average length and distance of a single ride for users have greatly improved. It has the characteristics of one-stop riding without transfer from the origin point to the destination and back home early. Compared to pre-COVID 19, the average distance of Beijing citizens riding a single trip has an increase of 69% to 2.38 kilometers (Sun, 2020).

O'Brien (2020) developed an online monitoring map since 2010, which shows the locations of docking stations associated with bike sharing usage from 400+ cities around the world, as shown in Figure 1. The map is generally updated every few minutes. There is a version that replays the last 24 hours of colour and size changes. Taking several European cities during morning peak period for example, the usage as well as the environment conditions can be obtained from this website as shown in Table 1.

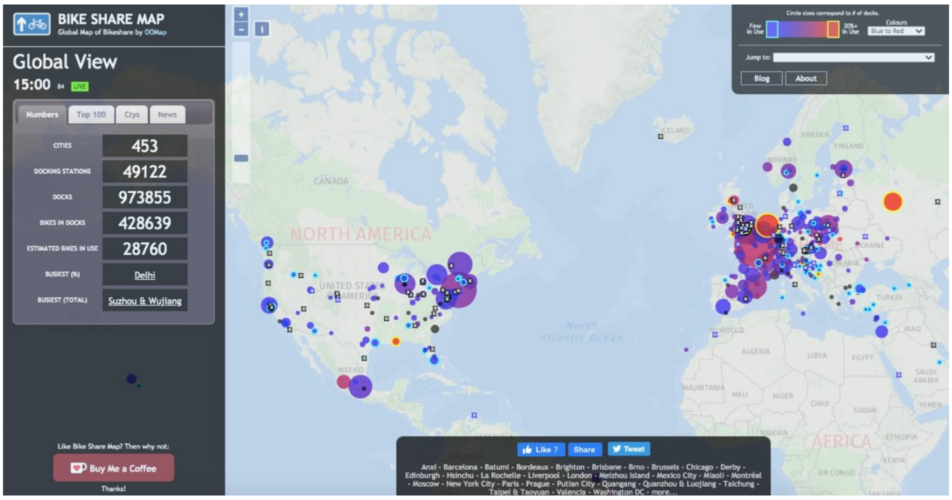

Figure 1 Bike sharing monitoring map (O'Brien, 2020)

Table 1 Bike sharing usage in several European countries around 8 am local time

Country	BSS	Bikes in use	Percentage	Condition
Paris	VÉLIB	753	9%	8°C / shallow fog
Milan	BIKEMI	404	9%	10°C / light drizzle
Barcelona	BICING	847	17%	12°C / party cloudy
Dublin	Dublin Bikes	76	20%	6°C / party cloudy
Brussels	Villo	106	6%	9°C / mostly cloudy
Vienna	Citybikes	54	7%	8°C / cloudy
Seville	Sevici	265	13%	15°C / fine
Valencia	Valenbisi	101	10%	16°C / mostly cloudy

3 Influence factors

A list of BSSs over the world is consolidated with numerous success-related factors such as coverage area, number of bikes, stations, population density and available infrastructure network. The duration was estimated by taking the difference between launching month and the latest month of operation. When the exact month is unknown, mid-year was used. Table 2 summarises the list of factors affecting the duration of bike sharing sustainability.

Table 2 List of factors

Index	Factor	Abbreviation	Factor type
I1	Coverage area	Area	Continuous
I2	System capacity	Capa	Continuous
S3	Population density	Pop	Continuous
S4	Purchasing power parity per capital	PPP	Continuous

	(PPP)		
S5	Climate	Clim	Discrete: 1. Frigid zone; 2. Temperate zone; 3. Sub-tropical zone; 4. Tropical zone
E6	Payment type	Pay	Discrete: 1. Other; 2. Month; 3. Pay-as-you-use; 4. Free first few hours followed by fixed rate
E7	Payment method	Pmeth	Discrete: 1. None/other; 2. ID; 3. Phone/bank number; 4. Coins/cash; 5. Smartcard/credit card
E8	Financial support	Fin	Discrete: 1. Private; 2. Public; 3. Combined; 4. Government

The most obvious factors should be *Infrastructural (I) factors* related to cycling infrastructure and cycling facilities. An estimation of the coverage area is used whereby the maximum horizontal and vertical spreads of the stations are first estimated and the rectangular area is calculated. The capacity of BSS is defined as the product of the number of bikes and stations, which were obtained from Wikipedia and each official website (List of bicycle sharing systems, 2020).

Social (S) factors include population density, purchasing power parity (PPP) per person, and climate, which can be obtained from city annual statistics reports. These factors can reflect the social and environmental conditions and shall have influence on travel behaviour.

Economic (E) factors refer to the ways of payment, payment method and financial support, which can be found from official website of each BSS and local news. These factors relate with the convenience of usage.

4 Methodology

4.1 Generalised linear model

A comparison between a list of bicycle-sharing systems from Wikipedia and bike share world map from Google Map is conducted to identify the operational status of the bike sharing systems. A group of student helpers was recruited to collect the required data from the internet (e.g. government report, operator’s annual report, newspaper, academic publications). Despite language barriers and insufficient information for some of the systems, a database of 106 systems with full required data was assembled for analysis, as indicated in Figure 2.

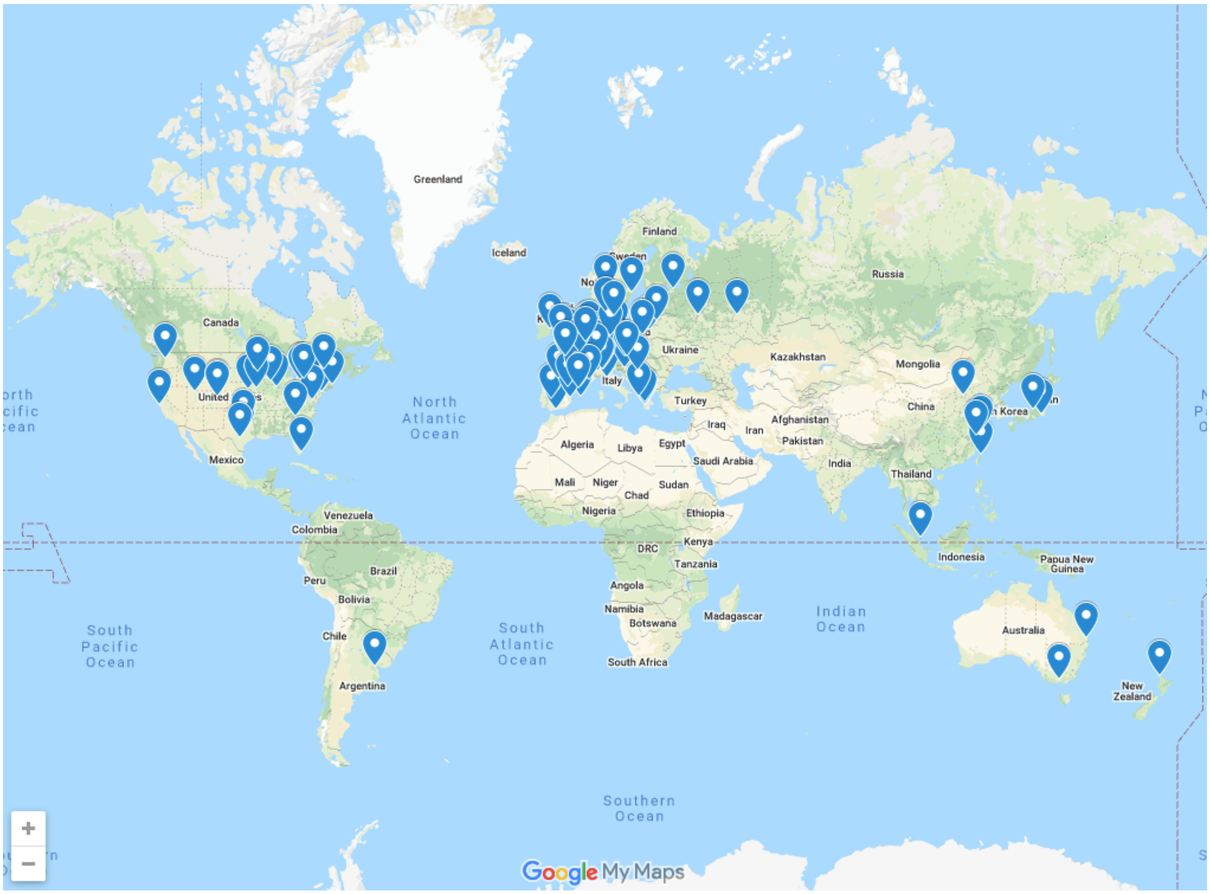

Figure 2 Study area (developed based on GoogleMap)

Various regression methods have been used successfully by previous researchers in applying different approaches to investigate the influence factors on cycling usage and cycling safety, such as linear regression (Xing et al., 2010), logit regression (Al-Ghamdi, 2002; Hunt and Abraham, 2007), Poisson regression (Wang and Nihan, 2004; Hels and Orozova-Bekkevold, 2007), binomial regression (Walter et al., 2011) and other models. The operation duration of a BSS can be considered as a random, non-negative and discrete event. Therefore, conventional linear regression models with a normally distributed error structure are not suitable for modelling the operation duration of a BSS. The Poisson regression in the generalised linear model (GLM) framework has been used more extensively (Cameron and Trivedi, 2013), which shall be used herein. In this study, the dependent variable is the duration of the BSS in operation. It is considered to be a good indicator of a successful BSS. The GLM with a Poisson error distribution can be formulated as follow:

$$Y = \mathrm{EXP}\left(\beta_0 + \sum_{i=1}^{i} \beta_i \times x_i\right) \tag{1}$$

where Y is the dependent variable of the duration of BSS; i is the subscript showing the index of independent variables; X is the independent variable; β_0 is the constant; and β_i is the coefficient of the independent variable, calculated in the calibration process of the model.

4.2 Results

To discuss the detailed influence factors for different stages of BSS, three groups are classified based on the status of the system, namely failed system, short duration on-going system (duration < 48 months), and long-duration on-going system (duration ≥ 48 months). Three GLM models are developed using STATA® software. Two kinds of comparison are conducted, failed system v. short duration on-going system, and short duration on-going system v. long-duration on-going system, to analyse the different factors and influence degree. The total number of BSSs collected for modelling is 366. Since quantitative data are scanty for some cities, the analysis sample constituting 18 failed systems, 39 short-duration on-going systems and 49 long-duration on-going systems are included in the model while the remaining 260 cities are excluded. Table 3 presents data of the analysis sample.

Table 3 Parts of research data

City	Y	I1	I2	S3	S4	S5	E6	E7	E8
Aigialeia	17	163,016	135	68	24,574	3	4	4	3
Aigle, Monthey	53	39,192	990	59	47,863	3	4	4	4
Ancient Olympia	17	1,187	240	25	24,574	3	4	4	3
Århus	101	11	22,800	2,854	37,794	3	4	1	3
Austin, Texas	13	16	4,400	2,758	54,980	2	4	4	3
Barcelona	94	51	2,544,000	15,991	30,637	3	4	4	4
Berlin	65	146	15,000	3,800	41,248	3	4	4	3
Białystok	5	80	9,000	2,900	21,118	3	4	4	3
Bordeaux	59	271	214,755	4,900	36,537	3	4	4	3
Boston, Massachusetts	41	105	124,300	5,151	54,980	3	4	4	4
Boulder, Colorado	41	13	2,760	1,524	54,980	3	4	4	3
Brisbane	52	31	300,000	140	44,346	2	4	4	3
Brussels	101	146	1,211,800	7,025	38,826	3	4	4	3
Buenos Aires	53	256	24,000	14,000	18,917	3	4	1	2
Caen	82	11	14,000	4,400	36,537	3	4	4	3
Chalon-sur-Saône	85	15	1,400	3,200	36,537	3	4	1	3
Chicago, Illinois	17	154	876,000	4,447	54,980	3	4	4	1
Clermont-Ferrand	17	12	4,840	1,600	36,537	2	4	4	4
Denver, Colorado	53	69	49,800	1,561	54,980	3	4	4	3
Dijon	83	11	15,600	3,800	36,537	3	4	4	3

(1) Failed system

Table 4 shows the descriptive statistics for the variables in failed systems. Table 5 gives the correlation matrix of the independent variables. No strong correlation exists amongst the selected independent variables included in the model.

Table 4 Descriptive statistics

	Variable	N*	Min	Max	Mean	Std. deviation
Y	Duration	18	6	48	21.44	14.69
I1	Area	18	11	480	186.44	138.73
I2	Capa	18	5	275,000	21562.78	64224.92
S3	Pop	18	17	15,140	3966.39	4479.83
S4	PPP	18	24,574	55,398	41227.50	7976.91
S5	Clim	18	2	3	2.94	0.24
E6	Pay	18	1	2	1.11	0.32
E7	Pmeth	18	1	5	2.89	1.97
E8	Fin	18	1	3	1.33	0.69

*N: Number of cities used

Table 5 Pearson correlation matrix

	I1	I2	S3	S4	S5	E6	E7	E8
I1	1							
I2	0.25	1						
S3	-0.40	0.10	1					
S4	-0.04	0.06	0.37	1				
S5	0.27	0.07	0.08	-0.11	1			
E6	0.08	-0.11	-0.01	0.00	-0.69	1		
E7	-0.26	-0.01	-0.39	-0.54	-0.27	0.02	1	
E8	-0.25	-0.16	-0.04	0.31	0.12	-0.18	-0.15	1

Table 6 shows the variables included in the model, their parameter estimates, and the significance of the parameters (5% level). The results show that the coverage area (Area), system capacity (Capa) and payment type (Pay) have significant effect on the success of BSS.

Table 6 Parameter estimates

Parameter	Coef.	Std.error	95% confidence interval		Hypothesis test	
			Lower	Upper	Wald Chi-square	Sig.
Intercept	1.63	1.69	-1.69	4.94	0.96	0.34
I1	-4.79E-03	7.51E-04	3.32E-03	6.26E-03	6.37	0.00
I2	-2.68E-06	7.40E-07	1.23E-06	4.13E-06	3.62	0.00

S3	1.61E-05	2.72E-05	-3.71E-05	6.94E-05	0.59	0.55
S4	7.25E-06	1.04E-05	-2.77E-05	1.32E-05	-0.70	0.11
S5	-0.13	0.47	-1.05	0.79	-0.28	0.78
E6	0.15	0.04	0.07	0.23	3.60	0.00
E7	0.09	0.24	-0.38	0.57	0.39	0.70
E8	0.28	0.12	0.05	0.52	2.39	0.12

Pearson statistic is used to test the goodness-of-fit of the model. The model has a P value of 0.14 which is not significant at 95% confidence level hence, there is insufficient evidence to reject the null hypothesis that the model well fits the data. The final model can be specified as follows:

$$\mathrm{Y} = \mathrm{EXP}(-4.79 \times 10^{-3} \times \mathrm{Area} - 2.68 \times 10^{-6} \times \mathrm{Capa} + 0.15 \times \mathrm{Pay}) \quad (2)$$

where Y is the duration of the BSS. This model can reflect the influence factors that affect the duration of failed BSSs. Among the three factors, coverage area and system capacity have negative parameter estimates, and thus they are inversely associated with success of BSS. That is, the coverage area and system capacity are not the more the better, and should be controlled within limitation. Payment type has positive parameter estimate, which plays an active role in ensuring the success of BSS. Cyclists prefer to pay the BSS with free first few hours followed by fixed rate.

(2) Short-duration on-going system

Table 7 shows the descriptive statistics for the variables in short-duration on-going systems. Table 8 gives the correlation matrix of these independent variables. There is no strong correlation between the selected independent variables included in the model.

Table 7 Descriptive statistics

	Variable	N*	Min	Max	Mean	Std. deviation
Y	Duration	39	4	46	27.74	13.29
I1	Area	39	0.69	16,316	4265.63	26090.08
I2	Capa	39	56	1,584,000	83168.13	284888.00
S3	Pop	39	25	87,779	5553.42	14893.42
S4	PPP	39	11,553	54,980	37507.51	15189.26
S5	Clim	39	1	3	2.85	0.43
E6	Pay	39	2	3	2.92	0.27
E7	Pmeth	39	1	4	2.10	0.55
E8	Fin	39	1	4	3.08	0.62

*N: Number of cities used

Table 8 Pearson correlation matrix

	I1	I2	S3	S4	S5	E6	E7	E8
I1	1							
I2	-0.05	1						
S3	-0.06	0.09	1					
S4	-0.14	0.29	0.19	1				
S5	0.06	0.07	-0.27	0.00	1			
E6	0.05	0.08	0.08	0.18	-0.10	1		
E7	-0.03	-0.04	-0.03	-0.24	-0.37	-0.12	1	
E8	-0.02	-0.26	-0.03	0.08	-0.15	0.04	0.36	1

Table 9 Parameter estimates

Parameter	Coef.	Std.error	95% confidence interval		Hypothesis test	
			Lower	Upper	Wald Chi-square	Sig.
Intercept	1.50	0.61	0.29	2.70	2.44	0.02
I1	-2.73E-06	1.52E-06	-5.72E-06	2.48E-07	-1.80	0.05
I2	-4.03E-07	1.42E-07	-6.81E-07	-1.25E-07	-2.84	0.00
S3	3.12E-06	1.85E-06	-5.11E-07	6.75E-06	1.68	0.09
S4	7.27E-06	2.39E-06	2.59E-06	1.19E-05	3.04	0.00
S5	-0.07	0.08	-0.22	0.09	-0.81	0.42
E6	0.04	0.16	0.33	0.96	3.99	0.00
E7	0.06	0.07	-0.20	0.08	-0.80	0.42
E8	0.01	0.06	-0.12	0.11	-0.12	0.05

Table 9 shows the variables included in the model, their parameter estimates, and the significance of the parameters (5% level). The results show that the Coverage area (Area), system capacity (Capa), PPP per capital (PPP), payment type (Pay) and financial support (Fin) have effect on the sustainability of BSS. Pearson statistic is used to test the goodness-of-fit of the model. The model has a P value of 0.089 which is not significant at 95% confidence level hence, there is insufficient evidence to reject the null hypothesis that the model well fits the data.

Therefore, the final model can be specified as follows:

$$Y = EXP(1.50 - 2.73 \times 10^{-6} \times \mathrm{Area} - 4.03 \times 10^{-7} \times \mathrm{Capa} + 7.27 \times 10^{-6} \times \mathrm{PPP} + 0.04 \times \mathrm{Pay} + 0.01\mathrm{Fin}) \quad (3)$$

where Y is the duration of the BSS. This model can reflect the influence factors that affect the short-time sustainability of BSS after starting successfully, including system capacity, PPP per capital, payment type and financial support. Among these factors, coverage area and system capacity have negative parameter estimates, while PPP per capital, payment type and financial support have positive parameter estimates.

(3) Long duration on-going system

Table 10 shows the descriptive statistics for the variables in long duration on-going systems. Table 11 gives the correlation matrix of these independent variables. There is no strong correlation between the selected independent variables included in the model.

Table 10 Descriptive statistics

	Variable	N*	Min	Max	Mean	Std. deviation
Y	Duration	49	51	197	73.73	25.60
I1	Area	49	0.84	39,192	899.63	5587.17
I2	Capa	49	90	7,624	1692.31	2101.63
S3	Pop	49	59	1,324,169	30462.04	188708.40
S4	PPP	49	10695	79,785	39943.78	10070.50
S5	Clim	49	2	3	2.96	0.20
E6	Pay	49	1	3	2.73	0.49
E7	Pmeth	49	1	5	2.02	0.63
E8	Fin	49	1	3	1.61	0.76

*N: Number of cities used

Table 12 shows the variables included in the model, their parameter estimates, and the significance of the parameters (5% level). The results show that the Coverage area (Area), system capacity (Capa), PPP per capital (PPP), Payment type (Pay) and Payment method (Pmeth) have effect on the long-time sustainability of BSS. Pearson statistic is used to test the goodness-of-fit of the model. The model has a P value of 0.36 which is not significant at 95% confidence level hence, there is insufficient evidence to reject the null hypothesis that the model well fits the data.

Table 11 Pearson correlation matrix

	I1	I2	S3	S4	S5	E6	E7	E8
I1	1							
I2	-0.10	1						

S3	-0.03	0.25	1					
S4	0.12	-0.03	-0.14	1				
S5	0.02	-0.30	0.03	-0.06	1			
E6	0.08	0.07	0.08	0.10	0.10	1		
E7	-0.01	0.04	-0.01	0.11	0.01	0.09	1	
E8	0.07	0.01	-0.12	-0.19	0.17	0.11	-0.03	1

Table 12 Parameter estimates

Parameter	Coef.	Std.error	95% confidence interval		Hypothesis test	
			Lower	Upper	Wald Chi-square	Sig.
Intercept	3.96	0.32	3.33	4.58	12.43	0.00
I1	-9.41E-06	3.60E-06	-1.65E-05	-2.36E-06	-2.62	0.01
I2	2.77E-05	9.20E-06	-4.58E-05	-9.72E-06	-3.02	0.00
S3	5.37E-10	9.56E-08	-1.87E-07	1.88E-07	0.01	1.00
S4	4.51E-05	1.79E-06	-8.02E-06	-1.01E-06	-2.52	0.01
S5	0.17	0.10	-0.03	0.37	1.66	0.10
E6	0.10	0.04	0.02	0.17	2.63	0.01
E7	0.07	0.03	-0.12	-0.01	-2.46	0.01
E8	0.03	0.02	-0.08	0.02	-1.27	0.20

Therefore, the final model can be specified as follows:

$$\begin{aligned} \mathrm{Y} = \mathrm{EXP}(&3.96 - 9.41 \times 10^{-6} \times \mathrm{Area} + 2.77 \times 10^{-5} \times \mathrm{Capa} + 4.51 \times 10^{-5} \times \mathrm{PPP} \\ &+ 0.10 \times \mathrm{Pay} + 0.07 \times \mathrm{Pmeth}) \end{aligned} \tag{4}$$

where Y is the duration of the BSS. This model can reflect the influence factors that affect the long sustainability of BSS after starting successfully, including coverage area, system capacity, PPP per capital, payment type and payment method. Among these factors, coverage area has negative parameter estimate, while system capacity, PPP per capital, payment type and payment method have positive parameter estimates.

(4) Comparison

It can be found from the above three models that coverage area, system capacity and payment type influence the sustainability of a BSS on all stages. Coverage area has the negative parameter estimate, while payment type has the positive parameter estimate in the three models. It means that BSS should be planned within proper coverage area by using free first few hours followed by fixed rate. System capacity has a negative parameter estimate in the first two models (failed and short duration on-going), but a positive estimate in the last model (long duration on-going), which gives reality of ground situation. As there is not very large demand at the initial stage, system capacity should be designed within reasonable range. After the system has entered into a stable stage, system capacity should be expanded according to the growth demand.

Comparing the parameters between failed system and short duration on-going system, PPP per capital and financial support are the distinctive positive factors to influence the likelihood of success of a BSS. Higher PPP per capital and government support will contribute to the initial stage of the BSS. Comparing the parameters between short duration and long duration on-going system, financial support is not a significant factor that will affect the duration of BSS sustainability. The increasing demand may promote BSS's development even with less government support. Payment method is the factor that needs to pay attention after the system is stable. Cyclists prefer convenient payment method, such as smartcard or coins rather than phone or ID.

5 Conclusions

Bike sharing originated in Europe 45 years ago and has expanded to all over the world recently. Notable growth of bike sharing has promoted green mobility development. However, many obstacles need to be resolved to design and maintain a successful bike sharing system, such as: plan and build supportive bike sharing infrastructure, raise funding, anti-theft measures. This study uses 106 cities to investigate the influence factors that affect the success and sustainability of a BSS by GLM analysis. Three regimes of BSSs are examined, namely failed system, short duration on-going system and long duration on-going system. It is found that the influence factors are different at different stages of a BSS. At the initial stage, coverage area, system capacity, payment type and financial support should be the key points to focus. Coverage area and system capacity should be designed within proper range. With a successful start and operation, subsequent operation should emphasise on the coverage area, system capacity, payment type and payment method. System capacity could be expanded within a reasonable coverage area according to local conditions.

Although the calibrated models provide some insightful results, still there are some limitations which provide interesting future research opportunities. First, the database used in the model can be extended with more cases and more quantitative variables, e.g. economic factors, socio-demographic factors. Second, the factors should be metricated with more detailed indicators. For example, there are only two variables used to present the infrastructure factor: coverage area and capacity. In fact, there are other indicators that should be considered, such as the availability of segregated cycling infrastructure, and the connectivity of bike infrastructure to public transport system. Further study can develop a more comprehensive performance evaluation framework to support the modelling. Third, relationship among variables can be explored for individual cases or a set of cases with similar features. It can provide more tailored information to support system operation. Last but not least, this study does not consider dockless BSS in the analysis. Dockless BSS seems to be on the way to dominate the bike sharing market globally. It should be worthwhile to investigate the key factors that may determine the success of dockless operation as well.

References

Alan, D. (2014). Bike share: what we've learnt from the Australian experience. Crikey, Austrialia. Access from: http://blogs.crikey.com.au/theurbanist/2014/06/05/bike-share-what-we%E2%80%99ve-learnt-from-the-australian-experience/

Al-Ghamdi, A. S. (2002). Using logistic regression to estimate the influence of accident factors on accident severity. *Accident Analysis & Prevention*,*34*(6), 729-741.

Cameron, A. C., & Trivedi, P. K. (2013). *Regression Analysis of Count Data* (No. 53). CambridgeUuniversity Press.

Audikana, A., Ravalet, E., Baranger, V., & Kaufmann, V. (2017). Implementing bikesharing systems in small cities: Evidence from the Swiss experience. *Transport Policy*, *55*, 18-28.

Chen, H., & Zhu, T. (2020). Co-governance of smart bike-sharing schemes based on consumers' perspective. *Journal of Cleaner Production*, 120949.

de Chardon, C. M., Caruso, G., & Thomas, I. (2017). Bicycle sharing system 'success' determinants. *Transportation Research Part A: Policy and Practice*, *100*, 202-214.

de Chardon, C. M. (2019). The contradictions of bike-share benefits, purposes and outcomes. *Transportation Research Part A: Policy and Practice*, *121*, 401-419.

DePillis, L. (2010). R.I.P., Smartbike, Good Riddance. Washington Citypaper. Access from: https://www.washingtoncitypaper.com/news/housing-complex/blog/13121154/r-i-p-smartbike-good-riddance

Fishman, E., Washington, S., Haworth, N., & Watson, A. (2015). Factors influencing bike share membership: An analysis of Melbourne and Brisbane. *Transportation Research Part A: Policy and Practice*, *71*, 17-30.

Hels, T., & Orozova-Bekkevold, I. (2007). The effect of roundabout design features on cyclist accident rate. *Accident Analysis & Prevention*, *39*(2), 300-307.

Hunt, J. D., & Abraham, J. E. (2007). Influences on bicycle use.*Transportation*, *34*(4), 453-470.

List of bicycle sharing systems (2020). In Wikipedia. Access from: http://en.wikipedia.org/wiki/List_of_bicycle_sharing_systems

ITDP. (2018). The Bikeshare Planning Guide. Access from : https://bikeshare.itdp.org/

Ji, Y., Ma, X., He, M., Jin, Y., & Yuan, Y. (2020). Comparison of usage regularity and its determinants between docked and dockless bike-sharing systems: A case study in Nanjing, China. *Journal of Cleaner Production*, *255*, 120110.

List of bicycle-sharing systems. (2020). Access from https://en.wikipedia.org/wiki/List_of_ bicycle-sharing_systems

Mattson, J., & Godavarthy, R. (2017). Bike share in Fargo, North Dakota: Keys to success and factors affecting ridership. *Sustainable Cities and Society*, *34*, 174-182.

Migliaccio, A. (2014). Rome's bike sharing programme is a bust. Busnessweek. Access from http://www.businessweek.com/articles/2014-06-19/romes-bike sharing-programme-is-a-bust

Moraes, T. (2011). RIO DE JANEIRO -- "Bike Rio" is the second incarnation of a bicycle hire programme for the Brazilian city after the first failed to take off. Will it convince Cariocas to pedal? Smartplanet. Access from: http://www.smartplanet.com/blog/global-observer/take-two-for-rio-de-janeiros-bicycle-rental-programme/

O'Brien. (2020). Global Map of Bikeshare by OOMap. Access from: https://bikesharemap.com

O'Sullivan, F. (2013). In Paris, thefts and vandalism could force bike-share to shrink. City Lab. Access from: http://www.citylab.com/commute/2013/09/paris-thefts-and-vandalism-could-force-bike-share-shrink/7014/

Ricci, M. (2015). Bike sharing: A review of evidence on impacts and processes of implementation and operation. *Research in Transportation Business & Management*, *15*, 28-38.

Schwartz, J.D. (2009). BIXI: Montreal's bicycle sharing system. The Urban Country. Access from: http://www.theurbancountry.com/2009/07/bixi-montreals-bicycle-sharing-system.html

Shi, J. G., Si, H., Wu, G., Su, Y., & Lan, J. (2018). Critical factors to achieve dockless bike-sharing sustainability in China: A stakeholder-oriented network perspective. *Sustainability*, *10*(6), 2090.

Si, H., Shi, J. G., Wu, G., Chen, J., & Zhao, X. (2019). Mapping the bike sharing research published from 2010 to 2018: A scientometric review. *Journal of Cleaner Production*, *213*, 415-427.

Sun (2020). The nation's first shared bicycle disinfection specification was issued. Access from: http://www.xinhuanet.com/politics/2020-03/16/c_1125716881.htm

Sun, F., Chen, P., & Jiao, J. (2018). Promoting public bike-sharing: A lesson from the unsuccessful Pronto system. *Transportation Research Part D: Transport and Environment*, *63*, 533-547.

The Straits Times. (2011). Bike sharing scheme back in the saddle. Access from: http://www.eco-business.com/news/bike sharing-scheme-back-in-the-saddle

Transport Canada. (2009). Bike sharing guide. Canada: Ministry of Transport. Access from: http://mobility-workspace.eu/wp-content/uploads/bsg.pdf

Walter, S. R., Olivier, J., Churches, T., & Grzebieta, R. (2011). The impact of compulsory cycle helmet legislation on cyclist head injuries in New South Wales, Australia. *Accident Analysis & Prevention*, *43*(6), 2064-2071.

Wang, Y., & Nihan, N. L. (2004). Estimating the risk of collisions between bicycles and motor vehicles at signalized intersections. *Accident Analysis & Prevention*, *36*(3), 313-321.

Xing, Y., Handy, S. L., & Mokhtarian, P. L. (2010). Factors associated with proportions and miles of bicycling for transportation and recreation in six small US cities. *Transportation Research Part D: Transport and Environment*,*15*(2), 73-81.

Yuan, M., Zhang, Q., Wang, B., Liang, Y., & Zhang, H. (2019). A mixed integer linear programming model for optimal planning of bicycle sharing systems: A case study in Beijing. *Sustainable Cities and Society*, *47*, 101515.

Zhang, J., Meng, M., & Wang, D. Z. W. (2019). A dynamic pricing scheme with negative prices in dockless BSSs. *Transportation Research Part B: Methodological*, *127*, 201-224.

Zhang, J., & Meng, M. (2019). Bike allocation strategies in a competitive dockless bike sharing market. *Journal of Cleaner Production*, *233*, 869-879.

Zhang, J., Meng, M., Wong, Y. D., Ieromonachou, P., & Wang, D. Z. W. (2020). A data-driven dynamic repositioning model in bicycle-sharing systems. *International Journal of Production Economics*, 231, 107909.