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Role of exposure in bicycle safety analysis: Effect of cycle path choice

Hongliang Ding

[a] Department of Civil and Environmental Engineering

The Hong Kong Polytechnic University

Hung Hom, Kowloon, Hong Kong

Email: hongliang.ding@connect.polyu.hk

N.N. Sze (Corresponding author)

[a] Department of Civil and Environmental Engineering

The Hong Kong Polytechnic University

Hung Hom, Kowloon, Hong Kong

Tel: +852 2766-6062; Email: tony.nn.sze@polyu.edu.hk

Yanyong Guo

[b] School of Transportation, Southeast University, China

[c] Jiangsu Key Laboratory of Urban ITS, China

[d] Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, China

Email: guoyanyong@seu.edu.cn

Haojie Li

[b] School of Transportation, Southeast University, China

[c] Jiangsu Key Laboratory of Urban ITS, China

[d] Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, China

Email: h.li@seu.edu.cn

ABSTRACT

Despite the recognized environmental and health benefits of cycling, bicyclists are vulnerable to severe injuries and mortalities in the road crashes. Therefore, it is of paramount importance to identify the possible factors that may affect the bicycle crash risk. However, reliable estimates of bicycle exposure are often not available for the safety risk evaluation of different entities. The objective of this study is to advance the estimation of exposure in the bicycle safety analysis, using the detailed origin-destination data of each trip of the London public bicycle rental system. Two approaches including shortest path method (SPM) and weighted shortest path method (WSPM) are proposed to model the bicycle path choice and to estimate the bicycle distance traveled (BDT). Then, the bicycle crash frequency models that adopt BDTs as the exposure estimated using SPM and three WSPMs are developed. Three exposure measures including bicycle trips, bicycle time traveled (BTT), and BDT are assessed. Results indicate that the bicycle crash frequency models that incorporate the BDTs using WSPM have superior model fit. Moreover, the bicycle crash frequency model that incorporate the BDTs as the exposure outperforms those that incorporate the bicycle trips and BTT as the exposures. Findings of current study are indicative to the development of bicycle crash frequency model. Moreover, it should enhance the understanding on the roles of environmental, traffic and bicyclist factors in bicycle crash risk, based on appropriate estimates of bicycle exposures. Therefore, it should be useful to the transport planners and engineers for the development of bicycle infrastructures that can improve the overall bicycle safety in the long run.

Keywords: Bicycle safety, exposure, bicycle distance traveled, bicycle crash prediction model, shortest path method

1. INTRODUCTION

Cycling has been increasingly promoted as a sustainable transport mode in many cities round the world. It does not only alleviate the traffic congestion and reduce the vehicle emissions, but also improves the health and well-being of the society (Menghini et al., 2010; Guo et al., 2019). For example, about 25% of the trips in Central London were made by bicycles in 2018. In Torrington Place, the bicycle share was 65% (Transport for London, 2018). Despite that, bicyclists are vulnerable to severe injuries and mortalities in the road crashes. As reported by Transport for London (2019), 16% of road casualties and 20% of road fatalities were bicyclists respectively.

Bicycle safety has received more and more attention in recent years. Studies have been conducted to identify the possible factors including built environment and bicycle facilities (Guo et al., 2018b; Wei and Lovegrove., 2013; Chen et al.,2016), population and household characteristics (Ghekiere et al., 2014; Vanparijs et al., 2015; Guo et al., 2018a), land use (Chen, 2015) and traffic attributes (Wei and Lovegrove., 2013) that may affect the bicycle safety. To better quantify the potential of bicycle crash involvement and interpret the risk of different entities, it is necessary to measure the crash exposure. In previous studies, bicycle exposures adopted were bicycle flow counts, bicycle trips (Miranda-Moreno et al., 2011), bicycle time traveled (BTT), and bicycle distance traveled (BDT) (Mindell et al., 2012; Poulos et al., 2015) which were measured using retrospective and prospective surveys. Regardless of sampling framework and survey design, data may be subject to recall and selection biases. In addition, an extensive household travel survey can be expensive and time-consuming. In a recent study, the transaction records of the London public bicycle rental system were used to estimate the bicycle crash exposure. Despite this system covered most bicycle trips in London, exposure measures were limited to bicycle trips and BTT (Ding et al., 2020).

In London, two cycle superhighways were introduced in 2010. They provided the faster, safer, and more direct routes for the bicyclists. The cycle superhighways are completely separated from the trafficable roads and footpaths. In addition, segregated crossings are provided at the intersections (Rayaprolu et al., 2020). The minimum width is 4 meters for a bi-directional cycle superhighway (European Cyclists' Federation, 2014). Currently, there are six cycle superhighways in London (Li et al., 2018). As illustrated in **Figure 1**, the total road length in London is 6,139 km. Cycle lanes (known as 'cycleway') are present on 8.1% (i.e. 496 km) of the roads. Overall, the total length of cycle superhighways in London is 77 km. Since the bicyclists do not only consider the path distance, but also the perceived safety and level-of-service when choosing the routes, it is expected that one would prefer the cycle superhighway to the traditional cycleway. The roads that have no cycle lane are expected to be the least preferred.

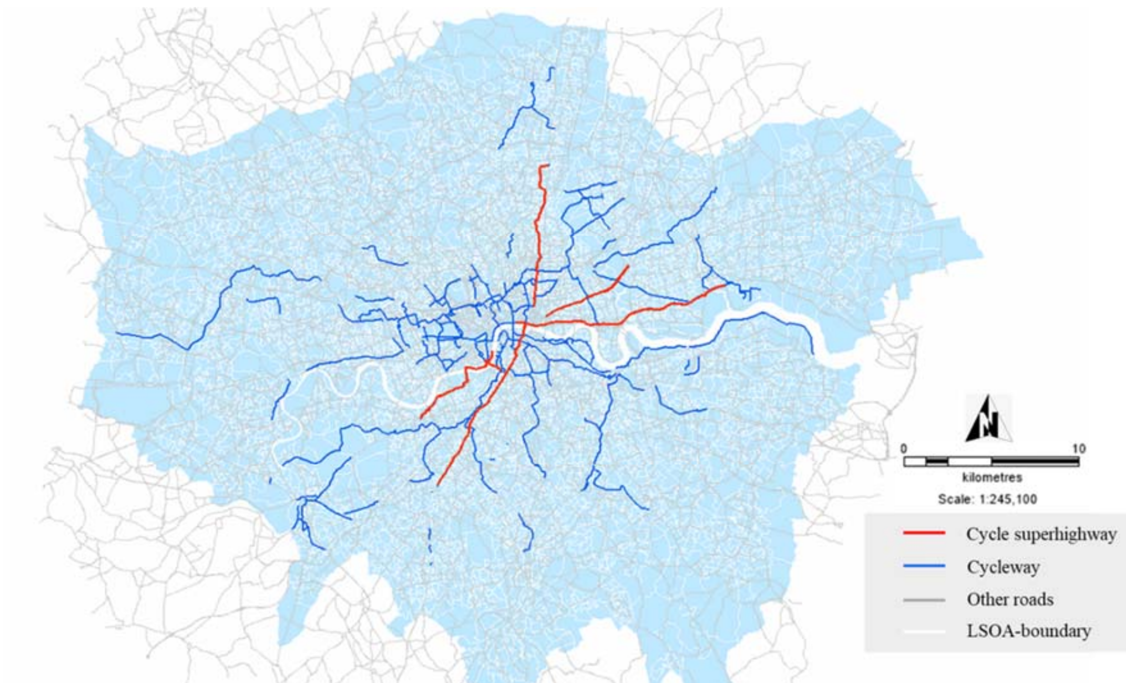


Figure 1. Illustration of London road network

In this study, the bicycle routing will be modeled, and the BDT will be estimated based on the origin and destination data of each trip of the London public bicycle rental system. Different from the vehicle drivers, the bicyclists generally consider multiple objectives including travel time and safety when choosing the route (Ehrgott et al., 2012). Two path analysis models: (a) the simple shortest path model (SPM) that incorporates the effect of path distance only; and (b) the weighted shortest path model (WSPM) that incorporates the effects of path distance and perceived safety level, in the route choices are proposed in this study. Then, the negative binomial regression models will be applied to assess the performances of the proposed bicycle path analysis models. Moreover, the associations between bicycle crash, various exposure measures (bicycle trips, BDT and BTT) and potential influencing factors will be estimated. Findings of this study would indicate the suitability of different bicycle exposure measures. Also, it can improve the understanding on the role of exposure in bicycle safety analysis.

The paper is organized as follows. Literature review is presented in **Section 2**. **Section 3** and **Section 4** describes the model formulation and method of data collection. The analysis results are then given in **Section 5**. Finally, the policy implications are discussed in **Section 6** and the concluding remarks are given in **Section 7**.

2. LITERATURE REVIEW

2.1 Bicycle safety covariates

Generally, the factors that affect the bicycle safety can be classified into three categories: environmental, traffic and human factors. For the environmental factors, land use, built environment and road infrastructures can affect the bicycle safety. For example, bicycle crash rates of the industrial and commercial areas are often higher than that of other land uses (Chen, 2015; Narayanamoorthy et al., 2013). In addition, the landscape, terrain and weather conditions can also affect the bicycle crash frequency (Vanparijs et al., 2015; Xing et al., 2019; Zhai et al., 2019). For the effect of traffic management, bicycle crash frequency is associated with the intersection density (Pulugurtha and Thakur, 2015; Wei and Lovegrove., 2013; Siddiqui et al., 2012; Saad et al., 2019; Lee et al., 2019a), presence of cycle lane (Hamann and Peek-Asa, 2013; Wei and Lovegrove.,2013; Reynolds et al., 2009; Bai et al., 2017; Fournier et al., 2019), and presence of traffic signal (Guo et al., 2020; Chen,2015; Deliali et al., 2020). For the effect of human factor, personal and household characteristics are associated with the crash involvement of bicyclists. For example, crash involvement rates of younger and older bicyclists are higher than their counterparts. This can be attributed to the variation in physiological capability and risk perception among individual bicyclists (Ghekiere et al., 2014; Siddiqui et al., 2012; Tin Tin et al., 2010; Rodgers, 1995; Lee et al., 2019b). Also, the fatality risk of male bicyclists is remarkably higher than that of female bicyclists (Wei and Lovegrove., 2013; Vanparijs et al., 2015; Guo et al., 2018b). Furthermore, household income can also affect the bicycle crash risk (Siddiqui et al., 2012; Guo et al.; 2018a).

For the association measure between bicycle crash frequency and possible influencing factors, it is necessary to consider the exposure to facilitate the accurate assessment and effective comparison. For example, cycling activities can vary across different built environments and road infrastructures. Unlike the vehicle crash analysis, automated bicycle counts are often not available for the estimation of bicycle exposure. In previous studies, population and population density were used to proxy the bicycle crash exposure at the macroscopic level (Wang et al., 2017; Lee et al., 2015; Cottrill and Thakuriah., 2010). Alternately, some studies used the total road length and length of cycle path to represent the exposure (Siddiqui et al., 2012; Wei and Lovegrove., 2013). However, these studies did not account for the differences in traffic flow between different roads and cycling activities between different population groups. To get rid of this, some studies adopted bicycle trips (Ding et al., 2020; Fournier et al., 2019; Miranda-Moreno et al., 2011; Guo et al., 2018b), vehicular traffic volume (Beck et al., 2007; Hamann and Peek-Asa, 2013; Wei and Lovegrove., 2013), BTT and BDT (Ding et al., 2020; Mindell et al., 2012; Poulos et al., 2015) as the exposure measure in bicycle crash analysis.

To measure the bicycle exposure, a possible way is to investigate the travel behavior (in term of bicycle trip, BTT and BDT) of specific bicyclist group using the questionnaire survey (Poulos et al., 2015). However, accuracies of the survey data, especially for time and distance traveled, are subject to recall bias. The BDT can be over- or underestimated. In contrast, bicycle trips, origin and destination data are more reliable. Therefore, it may be possible to estimate the BDT based on the shortest path between the origin and destination of each trip (Zacharias, 2005; Pucher and Buehler, 2006; Larsen and El-Geneidy, 2011).

2.2 Factors affecting bicycle route choice

For the route choice decision of motor vehicle drivers, common influencing factors are monetary cost, travel time and reliability. However, for the route choice decision of bicyclists, some other factors including road environment and level of service should also be considered (Ehrgott et al., 2012; Yang and Mesbah., 2013; Chen et al., 2017; Sener et al., 2009). For example, studies indicate that bicyclists tend to choose the routes that have less traffic signals and stop signs to avoid frequent stop-and-go (Heinen et al., 2010; Menghini et al., 2010; Stinson and Bhat., 2003). In addition, bicyclists tend to avoid the interactions with pedestrians and motor vehicles by choosing the routes that have less crosswalks and roadside parking (Stinson and Bhat., 2003; Yang and Mesbah., 2013). Furthermore, road geometric design including gradient and crossfall and road surface condition are also associated with the bicycle route choice (Sensor et al., 2009; Chen et al., 2017; Casello and Usyukov., 2014).

Nevertheless, the perceived safety risk can play an important role, as much as distance and time, in the bicycle route choice (Hopkinson and Wardman., 1996; Broach et al, 2012; Ehrgott et al, 2012). Possible factors that may affect the perceived safety risk of bicyclists are vehicular traffic flow and speed (Menghini et al., 2010; Gonza´lez et al., 2016). For instance, bicyclists tend to ride on the roads that have less vehicular traffic and lower speed limit (Sener et al., 2009). In addition, presence of bicycle infrastructures and facilities, including cycle lanes, cycle tracks, intersection crossing markings and corner refuge islands, is associated with the increase in bicycle use (Barnes and Thompson., 2006; Sener et al., 2009; Deliali et al., 2020; Ding et al., 2021). **Figure 2** depicts the typical bicycle facilities including (a) segregated cycle lane, (b) designated cycle lane, (c) shared bus and cycle lane, and (d) shared cycle lane and footpath. Several studies were conducted to examine the relationship between bicycle facility and bicycle route choice (Broach et al., 2012). Results indicate that bicyclists generally prefer segregated cycle lane to designated cycle lane. The shared cycle lanes are the least preferred choice (Jensen., 2007; Winters and Teschke., 2010). Moreover, directness and connectivity of the bicycle infrastructures can also affect the bicycle use. It is necessary to provide a direct and uninterrupted route for bicyclists to reach the desired destinations (Stinson and Bath, 2003). Last but not least, presence of protected intersections can improve the safety perception of bicyclists since the vehicular traffic are physically separated from the bicycles (Deliali et al., 2020).

(a) Segregated cycle lane

(Source: http://www.walkbikecupertino.org/new_wbc/index.php/2019/02/20/separated-bicycle-lanes-coming-to-mcclellan-road/)

(b) Designated cycle lane

(Source: https://ourhamilton.co.nz/on-the-move/council-take-steps-to-improve-cycle-lane-safety/

(c) Shared bus and cycle lane

(Source: https://future-economics.com/2019/03/24/bike-bus-lanes-can-i-interest-you-in-a-time-share/)

(d) Shared cycle lane and footpath

(Source: https://www.brooklynpaper.com/breaking-away-city-panel-green-lights-protected-pulaski-bike-lane/)

Figure 2. Illustrations of typical bicycle facilities

2.3 The current paper

Findings of previous studies indicate that bicycle trips, BTT and BDT are commonly used to proxy the exposure in bicycle safety analysis. Availability of extensive, accurate and reliable bicycle trip data is crucial. To this end, detailed transaction records of a public bicycle rental system were used to estimate the exposures (Ding et al., 2020). However, information on BDT is not available in the dataset. In this study, four path analysis models will be developed, i.e., shortest path method (SPM), weighted shortest path method 1 (WSPM1), weighted shortest path method 2 (WSPM2), and weighted shortest path method 3 (WSPM3), to model the bicyclist route choice and to estimate the BDT. Furthermore, the roles of three exposure measures, i.e. bicycle trips, BTT and BDT, that are played in the bicycle safety analysis would be investigated.

3 METHOD

In this study, the bicycle transaction records obtained from the London public bicycle rental system - Santander bikes are used to estimate the BDT. The dataset records the information on start time, end time, origin and destination of each bicycle trip. Then, the path of each trip would be determined using the SPM method. Considering the preferences of bicyclists to different bicycle infrastructures, the WSPM is also proposed to model the bicycle path. The model formulations of SPM and WSPM are given in the following sub-sections.

3.1 Bicycle path analysis

3.1.1 Simple shortest path model (SPM)

In this model, the shortest path is determined using the Dijkstra’s algorithm, assuming that a bicyclist would consider the path distance only in the route choice decision (Deng et at., 2012; Wang., 2012; Sedeño-noda and Colebrook., 2019; Liu and Chen., 2010). The key steps are given as follows.

Step 1: Let V denote the set of vertices of the road network in the algorithm. Denote C_{ij} as the weight that is assigned to the arc connecting V_i and V_j given by

$$C_{ij} = \begin{cases} \infty, \text{if no path between } V_i \text{ and } V_j \\ d_i, \text{otherwise} \end{cases}$$

where d_i denotes the distance of the shortest path originated from the vertex i, and is given by

$$d_i = L_{ij}$$

where L_{ij} is the connection distance between V_i and V_j.

Step 2: Let V_s be the source vertex which is labeled. Estimate the distance between V_s and other unlabeled vertices one by one, then an end vertex V_p will be identified when

$$d_p = min\{d_i | V_p \in V - S\}$$

where d_p is the distance of the shortest path from the source vertex to the end vertex, S is the set of labeled vertices of the shortest path, and (V-S) refers to all unlabeled vertices that are not 'visited' yet.

Step 3: When $V_p = V_t$, then d_p is the distance of the shortest path from V_s to the end point V_t, and the searching process can be stopped. Otherwise, assess another end point by,

$$d_i = min\{d_i, d_k + l_{kj}\}, V_p \in V - S, V_k \in S$$

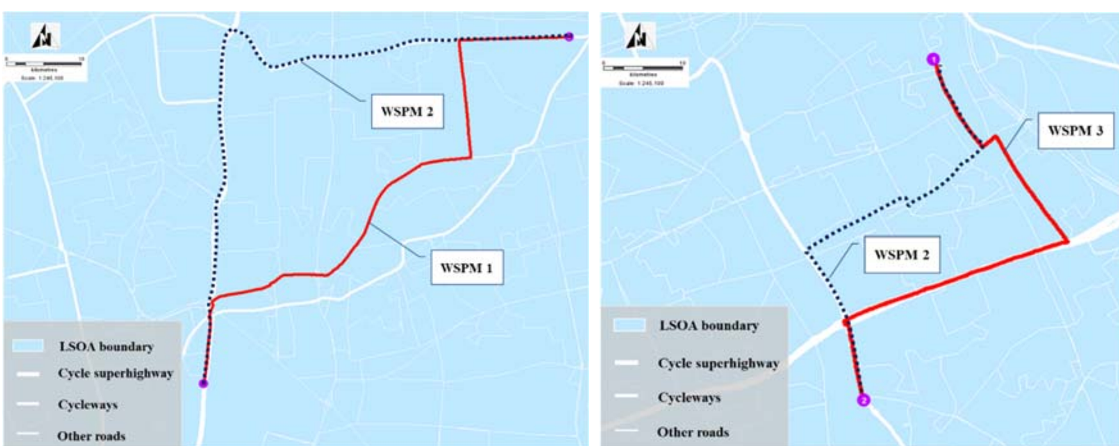
Step 4: Repeat step 2 and step 3 until $V_p = V_t$.

3.1.2 Weighted shortest path model (WSPM)

As mentioned above, not only the path distance, but also the perceived safety and level of service are considered in the bicycle route choice. In this study, it is assumed that cycle superhighway and cycleway are preferred by the bicyclists. Therefore, a weighted shortest path method (WSPM) is proposed, with which different weights are assigned to cycle superhighway, cycleway and other roads (that have no cycle lanes) respectively in the algorithm. As illustrated in **Table 1**, three different scenarios of weight allocation are considered: (i) WSPM1: Cycle superhighway is preferred, and there is no difference between cycleway and other roads; (ii) WSPM2: Cycle superhighway is the most preferred, followed by the cycleway, and other roads are the least preferred; (iii) WSPM3: Similar to WSPM2, just the differences in the weights are magnified. **Figure 3** shows an example of the bicycle path choice based on different WSPMs.

Table 1. Setting of different weighted shortest path model

Model	**Road type**				
	(A) Cycle superhighway		**(B) Cycleway**		**(C) Other roads**
WSPM1	W_A	>	W_B	=	W_C
WSPM2	W_A	>	W_B	>	W_C
WSPM3	W_A	>>	W_B	>>	W_C



(a) WSPM1 versus WSPM2 **(b) WSPM2 versus WSPM3**

Figure 3. Bicycle path choices using different WSPM

3.2 Bicycle safety analysis

Poisson regression method is often applied to model the crash frequency because of the random and non-negative nature of crash data. The mean and variance of Poisson distribution are assumed to be equal. When the variance is greater than the mean (i.e., over-dispersion), the negative binomial (NB) regression approach should be used (Mannering et al., 2016; Wong et al., 2007; Lee et al., 2019c; Lord and Mannering., 2010; Lord., 2006; Lord and Bonneson., 2007).

In this study, to evaluate the suitability of bicycle crash exposure, the BDTs estimated based on the SPM and WSPM would be incorporated into the bicycle crash prediction models using the Poisson and NB regression approaches.

For the Poisson regression model, probability of having *y* bicycle crashes in unit *i* at time *t* can be given by,

$$P(\mathrm{y}_{it}|\mu_{it}) = \frac{\exp(-\mu_{it})(\mu_{it})^{\mathrm{y}_{it}}}{\mathrm{y}_{it}!}$$

where $\mathrm{E}(\mathrm{y}_{it}) = \mu_{it}$ be the expected number of bicycle crashes.

On the other hand, the NB regression model can be derived by incorporating an error term that follows the gamma distribution into the probability density function, which is given by,

$$P(\mathrm{y}_{it}) = \frac{\Gamma(\mathrm{y}_{it} + \alpha^{-1})}{\mathrm{y}_{it}\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_{\mathrm{it}}}\right)^{\alpha^{-1}}\left(\frac{\mu_{it}}{\alpha^{-1} + \mu_{it}}\right)^{\mathrm{y}_{it}}$$

where $\Gamma(\cdot)$ is the gamma distribution with α being the over-dispersion parameter.

To assess the goodness-of-fit of the bicycle crash prediction models, Akaike information criterion (AIC) and Bayesian information criterion (BIC) are used. AIC and BIC are given as follows

$$AIC = -2\ln(L) + 2k \text{ and } BIC = \ln(n)k - 2\ln(L)$$

where L is the maximum likelihood function, n is the number of observations and k is the number of parameters.

4 Data

In this study, the observation unit of bicycle crash analysis is the Lower Super Output Area (LSOA) in London. LSOA is the primary unit for population census, public administration, and election in the United Kingdom. On average, each LSOA has a population of 1,500 people. Explanatory variables considered are land use, population characteristics, traffic flow and road infrastructure.

Bicycle crash data in the period between 2015 and 2016 are obtained from the Department for Transport (DfT)'s database. For each crash, information on road type, speed limit, lighting and weather condition, crash location, injury severity, and involvement of vehicles and other road users (i.e. pedestrians, bicycles, motor vehicles, etc.) are available. Also, information on the road network characteristics (i.e. road class and speed limit, etc.), traffic flow and traffic composition (i.e. private car, taxi, bus and goods vehicle, etc.) of all public roads are collected from the DfT's database. Therefore, the vehicle-kilometer (VKT) can be estimated.

In addition, information on the population profile, which are aggregated at the LSOA level, are available in the Office for National Statistics (ONS)'s database. For example, information on population and population density, poverty (i.e. Index of Multiple Deprivation, IMD), gender and age distribution are available. Moreover, information on land use (i.e. residential, commercial, and green area, etc.) are extracted from the ONS's database.

Furthermore, to examine the bicyclist travel behavior (i.e. trips and time), the transaction records of the London Public Bicycle Rental system - Santander Bike – in the period between 2015 and 2016 are used. As shown in **Table 2**, for each transaction, time duration, start time and end time, and origin and destination are recorded.

Table 2. Sample of bicycle rental transaction records

Transection ID	Duration (minute)	Bicycle ID	End time	Station ID (Destination)	Start time	Station ID (Origin)
40,346,512	120	7793	04/01/2015 00:03	450	04/01/2015 00:01	443
40,346,519	180	4643	04/01/2015 00:06	701	04/01/2015 00:03	680

40,346,508	360	12019	04/01/2015 00:06	424	04/01/2015 00:00	368
40,346,520	240	9978	04/01/2015 00:08	313	04/01/2015 00:04	98
……	……	……	……	……	……	……

The area of interest of the current study is illustrated in **Figure 4**. The study area is 49.1 km^2 and covers several Inner London Boroughs including City of London, Islington, Hackney, Tower Hamlets and Westminster. There are more than 750 docking stations in the study area. In 2017, the Santander Bike constituted about 74% of overall bicycle trips in London (TfL, 2018). The observation unit - LSOA is adopted to better characterize the spatial distributions of the population, land use and traffic characteristics. A total of 270 LSOAs are selected. The data from multiple sources are mapped to the corresponding LSOA using the geographical information system (GIS) approach. **Table 3** summarizes the characteristics of the LSOAs.

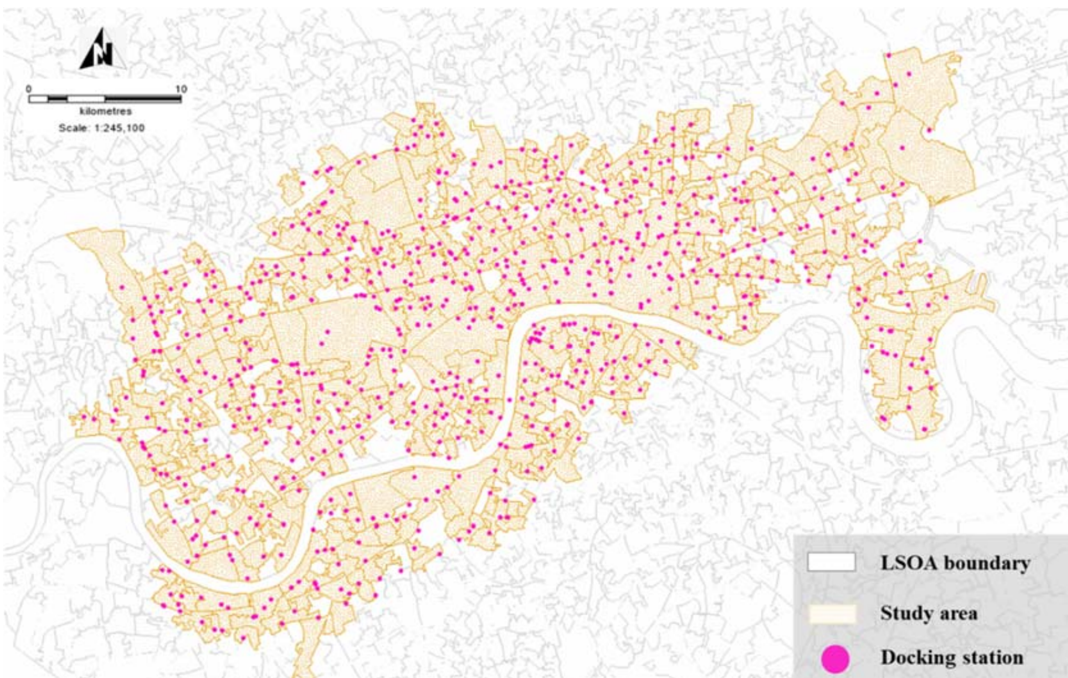


Figure 4. Location of the study area

Table 3. Summary statistics of the sample

Category	Factor	Attribute	Mean	Std. Dev.	Min.	Max.
Outcome	Frequency of bicycle crash		5.13	5.83	1	38
Land use	Proportion for		0.15	0.07	0.02	0.36

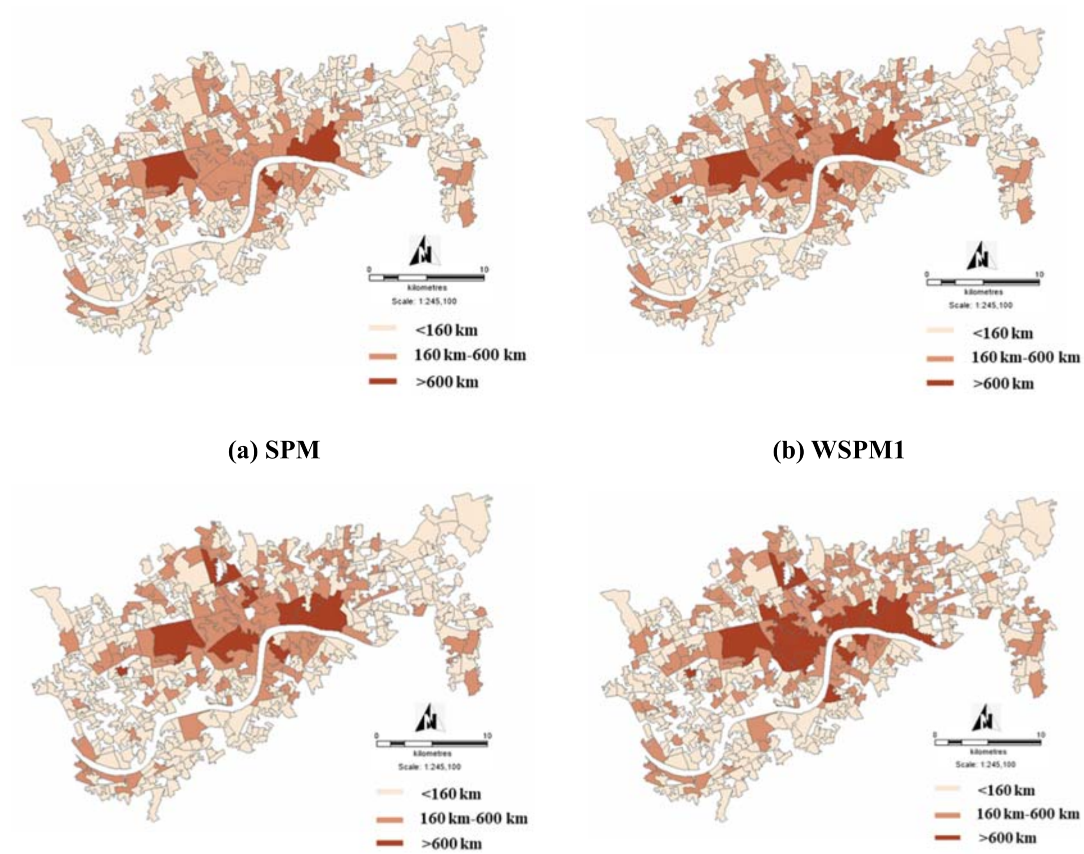
	residential					
	Proportion for commercial		0.25	0.14	0.01	0.56
	Proportion for green area		0.28	0.16	0.03	0.77
	Proportion for transport facilities		0.32	0.16	0.03	0.77
Population characteristics	Population density (per km^2)		14.28	7.36	0.86	39.77
	Population		1298	464	1077	3351
	Gender	Proportion of male	0.52	0.03	0.45	0.65
		Proportion of female	0.48	0.04	0.35	0.55
	Age	Proportion of age above 64	0.11	0.05	0.02	0.3
		Proportion of others	0.89	0.05	0.7	0.98
	IMD		24.49	10.46	6.06	53.20
Exposure	Annual BTT (hour)		10297	13434	163	14912
	Annual bicycle trips		28035	28748	544	236240
	VKT		45849	78965	51	712666

Note: Number of observations is 270

5 RESULTS

5.1 Estimation of BDTs

Figure 5 and **Table 4** illustrate the results of BDT estimations using SPM and WSPMs respectively. As depicted in **Figure 5(a)**, the BDTs seem evenly distributed across the whole study area, when the simple shortest path method is used. As expected, when higher weights are assigned to the cycleway (i.e. WSPM2) and cycle superhighway (i.e. WSPM3) in the bicycle path choice analysis, the BDTs would concentrate to the areas that have more cycleway (see **Figure 5(b)**) and cycle superhighway (see **Figure 5(c)**). Among the three WPSMs, as shown in **Table 4**, the total estimated BDT is the highest (annual average bicycle distance traveled of 159,600 km per unit) for the WPSM3, followed by the WPSM2 (150,100 km per unit) and then the WPSM1 (146,600 km per unit). This could be attributed to the higher operating speeds of cycle superhighway and cycleway. Therefore, the total estimated BDT tends to be higher given the same travel time.



(a) SPM **(b) WSPM1**

(c) WSPM2 **(d) WSPM3**

Figure 5. Distributions of BDTs by LSOA

Table 4. Estimation results of BDTs by LSOA (10^3 km)

Model	Mean	Standard Deviation	Maximum	Minimum
SPM	133.6	145.3	1,351.4	0.3
WSPM1	146.6	158.6	1,368.6	0.3
WSPM2	150.1	162.3	1,376.7	0.4
WSPM3	159.6	173.4	1,582.3	0.5

5.2 Bicycle crash analysis

To eliminate the heteroscedasticity among the variables, variables including population and

VKT are logarithmically transformed prior to the parameter estimation (Quddus, 2008). On the other hand, the multi-collinearity test is conducted to assess the correlations between the independent variables. Results indicate that the variance inflation factor (VIF) are less than five for all independent variables. Therefore, all candidate variables are considered appropriate.

5.2.1 BDTs as exposure (SPM versus WSPM)

Since the over-dispersion is prevalent for the data (mean = 5.13 and variance = 33.98), the bicycle crash prediction models, with which the BDTs are used to proxy the bicycle crash exposure, are established using the NB regression model. **Table 5** illustrates the model estimation results. As shown in **Table 5**, bicycle crash prediction models that incorporate the BDTs estimated by the WSPM are superior to that using the SPM, in accordance with the values of AIC and BIC, regardless of the weights assigned to cycleway and cycle superhighway. WSPM2 has the best model fit, with the lowest values of AIC (1268.48) and BIC (1305.46). In addition, differences in AIC and BIC between WSPM2 and SPM are all greater than 10 (Fabozzi et al., 2014). This implies that it is appropriate to assign a higher weight to cycle superhighway in bicycle route choice and safety analysis. Also, the over-dispersion parameter (0.172) of WSPM2 is significant at the 5% level. Therefore, it is appropriate to adopt the NB regression model. The marginal effects of BDTs on the bicycle crash frequency are also estimated (see **Table 6**). As shown in **Table 6**, bicycle crash frequency is more sensitive to the BDTs that are estimated using the WSPM as compared to that using the SPM. 1% increase in BDT is correlated with 0.47-0.70% increase in bicycle crash frequency when the WSPM is used. On the other hand, 1% increase in BDT is correlated with 0.11% increase in bicycle crash frequency when the SPM is used.

Table 5. Results of bicycle crash prediction models using BDTs as exposure

Category	Factor	WSPM1		WSPM2		WSPM3		SPM	
		Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant		-11.04**	-6.31	-10.98**	-6.45	-11.27**	-6.45	-10.79**	-6.13
Land use	Proportion of commercial area	2.41**	4.52	2.18**	4.17	2.37**	4.52	2.60**	4.89
	Proportion of green area	1.16**	2.80	1.05**	2.60	1.15**	2.81	1.24**	3.23
Population characteristics	log (population)	1.51**	3.12	1.38**	2.90	1.53**	3.19	1.58**	3.23
	Proportion of age above 64	IS	--	IS	--	IS	--	IS	--
	Proportion of male	5.77**	5.11	5.49**	4.98	5.69**	5.06	5.95**	5.22
	IMD	IS	--	IS	--	IS	--	IS	--
Exposure	log (VKT)	0.63**	7.01	0.59**	6.87	0.62**	7.21	0.64**	7.21
	BDT (km)	0.08*	1.92	0.14**	3.70	0.10**	2.48	0.02	0.53
Over-dispersion parameter	alpha	0.189		0.172		0.186		0.197	
Goodness-of-fit	AIC	1279.07		1268.48		1276.65		1282.45	
	BIC	1315.05		1305.46		1312.64		1318.43	

*Note 1: * and ** denote statistical significance at the 5% and 1% levels respectively.*

Note 2: IS denotes insignificant.

Table 6. Marginal effects of BDTs on bicycle crash frequency

Model	Elasticity	p-value
SPM	0.11	0.596
WSPM1	0.47	0.035
WSPM2	0.70	0.000
WSPM3	0.49	0.014

5.2.2 Bicycle trip, BTT and BDT as exposures

Three bicycle crash prediction models that incorporate bicycle trips, BTT and BDT respectively as exposure are also developed using the NB regression approach (see **Table 7**). As shown in **Table 7**, Model 3 which incorporate BDT as the exposure has the best model fit with the lowest values of AIC and BIC. Again, there are remarkable differences in AIC and BIC between Model 3 and Model 2 (both greater than ten). This indicates that model using BDT as the exposure is preferred. **Table 7** also shows that factors including road density, green area, commercial area, population and gender significantly affect the bicycle crash frequency at the 1% level. Such finding is consistent with that of many previous studies (Ding et al., 2020; Guo et al., 2018a; Chen, 2015; Wei and Lovegrove., 2013). Specifically, increases in the proportion of green area (1.05), proportion of commercial area (2.18), log (population) (1.38), proportion of male (5.49), log (VKT) (0.59) are associated with the increase in bicycle crash frequency. However, effects of IMD and proportion of elderly on bicycle crash frequency are not significant.

Table 7. Results of bicycle crash prediction models with different exposures

Category	Factor	Model 1		Model 2		Model 3	
		coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
Constant		-10.80**	-6.28	-10.78**	-6.19	-10.98**	-6.45
Land use	Proportion of commercial area	2.32**	4.41	2.39**	4.48	2.18**	4.17
	Proportion of green area	1.16**	2.86	1.16**	2.82	1.05**	2.60
Population characteristics	log (population)	1.46**	3.05	1.48**	3.05	1.38**	2.90
	Proportion of age above 64	IS	--	IS	--	IS	--
	Proportion of male	5.55**	4.95	5.61**	4.92	5.49**	4.98
	IMD	IS	--	IS	--	IS	--
Exposure	log (VKT)	0.59**	6.76	0.61**	7.01	0.59**	6.87
	Bicycle trips			0.10**	2.06		
	BTT (hour)	0.13**	3.10				
	BDT (km)					0.14**	3.70
Over-dispersion parameter	alpha	0.182		0.189		0.172	
Goodness-of-fit	AIC	1274.49		1278.56		1268.48	
	BIC	1309.29		1315.52		1305.46	

*Note 1: ** denotes statistical significance at the 1% level.*

Note 2: IS denotes insignificant.

Again, we have estimated the marginal effects of different exposures on bicycle crashes (see **Table 8**). As shown in **Table 8**, bicycle crash frequency is more sensitive to the BDT (WSPM2), as compared to bicycle trips and BTT. 1% increase in BDT is correlated with 0.70% increase in bicycle crash frequency. On the other hand, 1% increase in bicycle trips and BTT is correlated with 0.53% and 0.66% increases in bicycle crash frequencies, respectively.

Table 8. Parameter estimates for the effects of exposures on bicycle crash frequency

Exposure	**Elasticity**	**p-value**
BTT	0.66	0.002
Bicycle trips	0.53	0.025
BDT (WSPM2)	0.70	0.000

6 DISCUSSION

In previous studies, it is rare that bicycle crash exposure is incorporated into the bicycle crash prediction model, limited to the reliable bicycle count data. Taking the advantage of the availability of bicycle trip data obtained from the public bicycle rental system, we adopt various path analysis approaches to estimate the BDT as bicycle crash exposure.

6.1 SPM versus WSPM in estimating BDT

For the estimation of BDT, results indicate that the WSPM is superior to the SPM. Such result is reasonable since the SPM assumes that the bicyclists only consider path distance when making route choice decision. In contrast, the WSPM assigns different weights to different bicycle facilities. For example, higher weights are assigned to the cycleway and cycle superhighway, consider the fact that bicyclists would consider the connectivity, directness, environmental quality and safety when planning the travel routes (Ehrgott et al., 2012; Broach et al., 2012; Hopkinson and Wardman., 1996).

Among the WSPMs, WSPM1 has the worst model performance with the highest values of AIC and BIC. It is because such assignment approach is contradicting with conventional wisdom that the perceived safety level of the cycleway is higher than that of the roads that have no cycle lane. Indeed, the revealed safety level of the former is 28% higher than that of the latter. Additionally, many studies also indicate that the bicyclists are more willing to ride on the cycleway (Lusk et al., 2011, Broach et al., 2012; Winters and Teschke., 2010). Nevertheless, the bicycle crash frequency models that incorporate the BDT based on WSPM2 ($W_A>W_B>W_C$) is superior to that based on WSPM3 ($W_A>>W_B>>W_C$). The latter hypothesizes that preferences towards cycleway and cycle superhighway are more substantial. It implies that the bicyclists would give up the safety and level of service by riding on the roads that have no cycle lane only if the time saving and/or the reduction in total travel distance was considerable. However, such speculation might be controversial.

Indeed, several studies indicate that there is no noticeable difference in traffic safety among cycleway, cycle superhighway and other roads that have no cycle lane (Li et al., 2017). It could be because of the heterogeneity in the preference among the bicyclists. For example, even the occasional bicyclists generally prefer the cycleway and cycle superhighway, the commuting cyclists may have some other considerations (i.e. route directness and attractiveness) when making the route choice (Ehrgott et al., 2012; Howard and Burns., 2001). Moreover, studies also show that the cycleway is not always considered as more desirable than a wider arterial road for the experienced bicyclists (Taylor and Mahmassani., 1996; Heinen et al., 2010). Furthermore, factors like gender can also affect the safety perception and bicycle route choice (Gonza´lez et al., 2016; Sener et al., 2009; Stinson and Bhat, 2003; Krizek et al., 2004). It is therefore worth exploring the effects of individual characteristics and trip purpose on the association between route choice and road attributes using the bicyclist survey in the future study.

6.2 Bicycle crash exposures

We also assess the use of bicycle trips, BTT, and BDT as exposures in the bicycle crash analysis.

Results indicate that bicycle crash frequency model using the BDT as the exposure provides the best model fit. It is because trip distance is more sensitive to the interactions between bicycle and other road users, and therefore potential traffic conflicts, as compared to trip frequency (Pei et al., 2012). Indeed, there is no noticeable difference in the elasticities between BTT and BDT (see **Table 8**).

In this study, factors including land use, population characteristics and traffic conditions that affect the bicycle crash frequency at zonal level are considered. Results show that the proportion of commercial area (2.18) and green area (1.05) are positively correlated with bicycle crashes. This can be attributed to the frequent pick-up and drop-off activities at the roadsides in the commercial area (Ding et al., 2020). As for the effect of green area, it is not surprising since considerable portion (31%) of bicyclists in London report that they ride for recreation purpose (TfL., 2015). In addition, log (VKT) (0.59) is positively associated with bicycle crashes. It is consistent with that of previous study (Alkahtani et al., 2018), since the interactions between vehicles and bicycles can increase with the traffic volume. Furthermore, the increase in the proportion of male (5.49) is associated with the increase in bicycle crash frequency. This can be attributed to the difference in safety perception and cycling behaviors among different bicyclist groups (Guo et al., 2018b). Nevertheless, current study is limited to the average effect of built environment on bicycle safety at the macroscopic level (i.e. LSOA). It is worth exploring the moderating effect of geometric design and road environment on the association between bicycle crashes and BTT and BDT, when detailed crash, traffic and environment data at the microscopic level is available in the future study. On the other hand, it is worth noting that crash occurrence is rare. It is often necessary to accumulate more bicycle crashes over a considerable period when evaluating the safety effect of an intervention. To this end, it is possible to evaluate the bicycle safety level using appropriate surrogate safety measures, e.g. conflicts (Sayed et al., 2013; Kassim et al., 2014; Christofa et al., 2019; Strauss et al., 2017; Guo et al., 2020).

7 CONCLUSION

To assess the bicycle crash risk of different entities and better interpret the relationship between bicycle safety and possible risk factors, it is necessary to have reliable exposure measures such as bicycle count number, bicycle trips, BTT, and BDT. Unlike vehicular crash analysis, extensive bicycle counts are often not available. In a recent work, detailed transaction data of the London public bicycle rental system was available to estimate the bicycle crash exposure (i.e., BTT and bicycle trips) at the zonal level, using the data on bicycle trip, origin and destination (Ding et al., 2020). In this study, we revisit the topic of bicycle crash exposure by estimating the BDT of each trip using the shortest path method. Considering the effects of safety perception, attitudes and preferences to different bicycle infrastructures on bicycle route choice, a modified path analysis approach – weighted shortest path method – is proposed.

Results indicate that the bicycle crash frequency model that adopts BDT as the exposure is superior, compared to that using bicycle trips and BTT as the exposures. In addition, the bicycle crash frequency models that adopt BDTs estimated using the WSPM apparently have better model fit, compared to that using the SPM. For instance, when the differences between the preferences toward cycle superhighway, cycleway and other roads are moderate, the best model fit can be attained. This justify that bicyclists do not only consider path distance, but also other factors such as level of service and perceived safety when choosing the routes (Ehrgott et al., 2012; Broach et al., 2012). Indeed, safety perception may vary across individuals and trip purposes, and the uncertainty in the route choice can be considerable (Heinen et al., 2010; Gonza´lez et al., 2016; Sener et al., 2009). In this study, we consider only the effect of the presence of cycle superhighway and cycleway on bicycle exposure limited to available data. It is worth investigating the factors including bicycle infrastructure, traffic volume and perceived safety of bicyclists (Ehrgott et al., 2012; Yang and Mesbah., 2013; Menghini et al., 2010; Gonza´lez et al., 2016) that may affect the bicycle exposure when required data is available. In addition, the bicycle exposures are estimated based on transaction records of a public bicycle rental system in London - Santander Bike. Despite that the Santander Bike system constitutes over 70% of bicycle trips in the study area, results of parameter estimation can be subject to bias because there may be difference in the behaviors between different bicyclist groups. This can be overcome when comprehensive bicycle count data are available. On the other hand, current study focuses on the relationship between bicycle crash frequency, exposure and possible risk factors at the zonal level. Effect of the uncertainty in route choice on the association measure can be incremental. Nevertheless, it is worth exploring the effect of the variation in route choice on the space-time evolution of bicycle trip distance, and therefore the bicycle crash exposure at the microscopic level, e.g. road segment, in the future study. Furthermore, this study does not consider the bicycle crash severity. Indeed, under reporting of bicycle crashes is prevalent, especially for the single bicycle and minor injury crashes (Tsui et al., 2009). In the future study, heterogeneity in the bicycle crash risk by collision type and injury severity would be investigated.

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