Quantitative Evaluation on Public Bicycle Trips and its Impact Variables among Different Land Uses

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Received: July 24, 2019; Accepted: December 16, 2019
Key words: Public bicycle sharing system, Trip productions, Land use, Linear regression model

Abstract: Public bicycle sharing systems for daily use have been effective for increasing cycling in China, which can significantly ease traffic congestion and the production of toxic gases. Encouraging the development of bicycle transportation has become an important part of cities’ sustainable development policies. This paper explains the relationships among public bicycle trips, public infrastructure, road characteristics, the built environment, and temporal variations. The study area is the Xisha Education District, which is located in the east of Hangzhou City, China. Using data on the Hangzhou Public Bicycle system, we utilized Pearson correlation analysis and multiple linear regression modelling to analyse how the variables affect public bicycle trip production for different land uses. This paper also analyses the temporal variations for hourly trip production for three land uses. The results show that public infrastructure and road characteristics significantly affect public bicycle trips. In addition, the effects of temporal variation vary across different land uses. Our findings will be helpful for planners and engineers to improve their understanding of public bicycle production.

1. INTRODUCTION

In recent years, the increase in the number of vehicles on the road has increased the convenience of travel; however, at the same time, it has also caused numerous social and environmental issues such as pollution, resource consumption, traffic jams, and other negative effects. The support for daily-use public bicycle sharing systems is a useful way to support urban sustainability. Public bicycle sharing systems appeared in Amsterdam in the 1960s (Dell’Amico et al., 2018) and were promoted in several cities in the world from 2006 (Fishman, 2016). In European cities such as Paris and Copenhagen, bicycle traffic has been promoted (Si et al., 2019). Many cities in China have also re-emphasized the role of bicycle transportation. Encouraging the development of bicycle transportation has become an important part of cities’ sustainable development policies. Sharing systems mean that public bicycles can be easily picked up without worry about parking or theft. Combined with public transportation, public bicycle sharing systems provide a way to settle the last-mile problem (Shi et al., 2018)

Such systems have developed rapidly in cities such as Hangzhou and Shanghai. Hangzhou is a famous tourist city in China, and improving the urban environment is an important mission of urban construction. To solve
problems related to increasingly difficult travel, under the leadership of the Hangzhou Municipal Government, a public bicycle sharing system was added to the city's public transportation system (Pan et al., 2010). The government is a strong supporter and promoter of the public bicycle system, which was constructed and is managed by a bicycle traffic company. The Hangzhou Government has formulated priority policies for public bicycle system investment. To ensure the construction of public bicycle stations, the municipality has invested 180 million yuan (Shaheen et al., 2011). The preferential policies mean the sharing system can be used with certain modes of public transportation, which greatly facilitates its use by travellers. The system is available 24 hours a day, and the use of public bicycles is free for one hour. Daily usage and frequency of usage of public bicycles and the satisfaction of residents with the system have rapidly increased (Wang, Q. & Chen, 2007). In addition, compared with other countries, the construction of urban public bicycle sharing systems in China has been rapid and on a large scale (Geng et al., 2009).

Since the number of public bicycle trips has grown across the world, studies focusing on public bicycle sharing systems are growing (Wang, K., Akar, & Chen, 2018). In the past few years, several studies have focused on variables that affect public bicycle usage. Buck and Buehler (2012) analysed the relationships between public bicycle trips and bicycle lane supply with control variables in Washington, DC. They found a significant correlation between bicycle lane supply and public bicycle trips. Spatial and temporal interaction was also found to influence bicycle station demand (Faghih-Imani & Eluru, 2016). In Montreal, Faghih-Imani et al. (2014) examined the determinants (i.e., meteorological data, temporal characteristics, bicycle infrastructure, land use, and the built environment) of the BIXI public bicycle system. In terms of its temporal characteristics, they found that people ride more on weekdays and in the afternoon and evening periods than at other times. Moreover, the results show that public bicycle usage increases with more public bicycle facilities such as public bicycle stations. Faghih-Imani and Eluru (2016) also developed a multinomial logit model to explore the impact of land use and public transportation infrastructure. Wang, K., Akar, and Chen (2018) examined the relationship between the built environment and public bicycle trips across different age cohorts using zero-inflated negative binomial models. They also captured the temporal variation and discovered that public bicycle trips are frequently made during rush hours. Krykewycz et al. (2010) hypothesized on three main factors that contribute to trip production, namely population, land use, and spatial attributes of infrastructure. Faghih-Imani et al. (2017) also used these three factors. Noland, Smart, and Guo (2016) examined the effects of population, public bicycle infrastructure, and public transportation infrastructure on public bicycling and forecasted trips. The authors found proximity to public transportation infrastructure or the availability of more bicycles is associated with more public bicycle usage.

Despite the growth of research on public bicycling in recent years, few studies have examined the relationship between public bicycle trip production and the impact of variables separately for different land uses, especially considering the assertion that trip production behaviour may differ by land use. This research builds on the previous studies mentioned and attempts to further understand how the variables of public bicycle trip production vary by land use. This will help operators better understand supply and demand for public bicycles. We explain the relationship among public bicycle trips, public infrastructure, road characteristics, and temporal
variation for residential, educational, industrial, and commercial land uses. We selected Hangzhou as the study area because of its popularity and large number of public bicycles in use. Using data from the Hangzhou Public Bicycle systems, we analysed how road characteristics affect public bicycle trip production for different land uses using multiple linear regression modelling. We also analyse temporal variations in the characteristics of hourly trip production for three land uses. The results show that some road characteristics significantly affect public bicycle usage. In addition, the effects of temporal variations vary across land uses. The findings of this study can help to identify variables that will increase the number of public bicycles in use in Hangzhou as well as provide advice regarding station size and location decisions. Our findings will be helpful for planners and engineers so they can improve their understanding of public bicycle trip production.

The remainder of the paper is organized as follows. Section 2 describes the study area, data collection, and research methods. Section 3 presents the results of our study and discusses these, and Section 4 presents our conclusions and some limitations.

2. DATA AND METHODS

2.1 Data

The Hangzhou Public Bicycle system was the first public bicycle sharing system in China and one of the largest in the world (Press, 2011). By 2018, 3,855 bicycle stations and 86,600 bicycles had been put into use in Hangzhou City (Hangzhou Public Transport Group, 2018). The use of public bicycles is free for the first hour, the second hour costs about $0.15, and the third hour is around $0.30, however the initial application to use the public bicycle system requires a $30 deposit (Shaheen et al., 2011). With smart-card technology, the system tracks the current usage for each bicycle station (departure and arrival). In this study, using crawler software, we captured hourly bicycle sharing usage data (from 07:00 to 20:00) from 78 bicycle stations during the period from 8th May 2015 to 14th May 2015 (seven days). The stations the data were collected from are all located in the Xiasha Education District. The bicycle usage data includes information on the production/departure bicycle station, the attraction/arrival bicycle station, and hourly trip data. Overall, the dataset consists of production data for 7,098 hourly trips as the dependent variable.

2.1.1 Overview of the study area

Hangzhou is located in the southeast of China (Figure 1). It is the capital city of Zhejiang Province and an important city in the Yangtze River Delta metropolitan area. The study area, Xiasha Education District (a subdistrict of Jianggan District in Hangzhou), is an industrial and educational centre located in the east of Hangzhou (Figure 1) 19.5 kilometres away from the city centre. Several bus lines and one subway line connect Xiasha District with the city centre. Xiasha Education District has a population of 420,000 and a developed area of 47 square kilometres (Hangzhou Xiasha Government, 2018). There are 14 universities and several industrial companies in the study area. Most of the companies are focused on optical
equipment, laptops, and automobile products. Travel behaviour is influenced by land use (Boarnet & Crane, 2001; Zegras, 2004) and thus it is unnecessary to analyse how road characteristics affect public bicycle trip production for different land uses. We chose four main land uses in Xiasha District, namely industrial, educational, residential, and commercial areas. The information on land use was collected by the Xiasha neighbourhood community.

Figure 1. The study area

2.1.2 Temporal and infrastructure variables

It is generally believed that public bicycle usage should be measured by a set of variables rather than a single variable. In this study, we chose public bicycle infrastructure, public transportation infrastructure, and temporal variations as explanatory independent variables for analysis in different land uses. The locations of public bicycle infrastructure and bus stops were downloaded from Baidu Maps. However, the Baidu coordinates are Mars coordinates (a geodetic datum formulated by the Chinese State Bureau of Surveying and Mapping); for accurate analysis, we transformed these into WGS84 coordinates. Figure 2 shows the locations of public bicycle infrastructure and bus stops. According to previous research, a comfortable walking distance is 400 to 500 meters (McCormack, Giles-Corti, & Bulsara, 2008). Therefore, we created a 500-meter buffer for each bicycle station and calculated the number of bicycle stations and bus stops inside it (Table 1). The distance to the nearest bus stop was also used as a variable in the analysis. In addition, we analysed the relationship between temporal variation characteristics and hourly trip production. The temporal variations include hourly usage data for each bicycle station divided into AM (07:00 - 09:00), Midday (09:00 - 12:00), PM (12:00 - 16:00), Evening (16:00 – 20:00), Weekdays, and Weekend. The temporal variables are represented by dummy variables. All the data shown in Table 1 were calculated by ArcGIS 10.0.

2.1.3 Road characteristics and built environment variables

In addition to the above variables, the road characteristics and building environment are also important. In this study, based on the 500m buffer of each bicycle station, we used the number of intersections, road length, and bicycle route length as explanatory independent variables (Table 1).

To quantify the built environment, we used point of interest (POI) data collected from Gaode Map in 2015 with a total of 30,882 records (Figure 3). The initial POI types were summarised into eight categories according to Long and Zhou (2016): commercial sites, office buildings, transport facilities, government buildings, education buildings, residential
communities, green space, and others. For indicators of the built environment, we used diversity and density, as proposed by Cervero and Kockelman (1997). The equations for diversity and density are shown below in the next section. The descriptive variables are shown in Table 1.

Table 1. Descriptive variables

| Variables                              | Mean | Std.* | Min | Max |
|----------------------------------------|------|-------|-----|-----|
| Temporal                               | -    | -     | -   | -   |
| 7:00-9:00                              | -    | -     | -   | -   |
| 9:00-12:00                             | -    | -     | -   | -   |
| 12:00-16:00                            | -    | -     | -   | -   |
| 16:00-20:00                            | -    | -     | -   | -   |
| Weekday                                | -    | -     | -   | -   |
| Weekend                                | -    | -     | -   | -   |
| Infrastructure                         | -    | -     | -   | -   |
| Number of bicycle stations within a 500m buffer | 1.08 | 0.92  | 0   | 4   |
| Number of bus stops within a 500-m buffer | 5.28 | 4.26  | 0   | 18  |
| Distance to nearest bus stop (in meters) | 313.01 | 373.29 | 0.52 | 2308.25 |
| Road characteristics                   | -    | -     | -   | -   |
| Number of intersections within a 500m buffer | 3.52 | 1.41  | 1   | 7   |
| Length of roads (in km) within a 500m buffer | 5.75 | 2.55  | 1.54 | 11.05 |
| Length of bicycle routes (in km) within a 500m buffer | 3.85 | 1.46  | 1.54 | 8.62 |
| Building environment                   | -    | -     | -   | -   |
| Diversity                              | 0.854 | 0.254 | 0.412 | 1.4 |
| Density                                | 828.53 | 756.75 | 11.46 | 2826.59 |

* Standard Deviation

Figure 2. The distribution of bicycle stations and bus stations

Table 2 summarizes trip production for different land uses. The maximum public bicycle trip production is in industrial areas, with 33 bicycle stations. Public bicycle trip production in educational areas is almost the same as in industrial areas, but these areas have only 18 bicycle stations. In residential areas, 9,601 public bicycle trips were produced, with 20 bicycle stations.
Table 2. Trips across four land uses in one week.

| Number of stations | Total trip production | Percentage of trips |
|--------------------|-----------------------|---------------------|
| Industrial areas   | 33                    | 10,711              | 30.7%               |
| Educational areas  | 18                    | 10,686              | 30.6%               |
| Residential areas  | 20                    | 9,601               | 27.5%               |
| Commercial areas   | 7                     | 3,864               | 11.2%               |
| Total              | 78                    | 34,862              | 100%                |

2.2 Methods

The temporal variables are dummy variables. The infrastructure and road characteristic variables shown in Table 1 were calculated by ArcGIS 10.0. The indicators for calculating diversity include the dissimilarity index (Cervero & Kockelman, 1997) and information entropy (Sung, Lee, & Cheon, 2015). Density is defined as the ratio between the total number of POI in an area. The equations for diversity (DI) and density (DE) are as follows.

\[
DI = \sum S_n \times \ln \left( \frac{1}{S_n} \right)
\]

where \( n \) is the category of POI, \( S_n \) is the ratio between the number of POI in a single category to the total number of POI.

\[
DE = \frac{n_i}{N_i}
\]

where \( n_i \) is the total number of POI, and \( N_i \) is the area.

In this study, we calculated the hourly trip data for each bicycle station in different land use areas. To explore the relationship between our variables and trip production, we first conducted Pearson correlation analyses. In statistics, this is a bivariate correlation analysis widely used in the sciences (Edwards, 1976; Kenney, 1939; Cohen et al., 2003). The Pearson correlation coefficient describes the linear correlation between two variables, \( a_i \) and \( a_j \) (Bevington et al., 1993; Rodriguez-Lujan et al., 2010) and ranges from -1 to 1, where -1 or 1 is the total negative or positive linear correlation and 0 is no correlation. The Pearson correlation coefficient between a pair of variables \( a_i \) and \( a_j \) is defined as:

\[
P(a_i, a_j) = \frac{\text{cov}(a_i, a_j)}{\sigma_{a_i} \sigma_{a_j}}
\]

Figure 3. The distribution of points of interest
where $cov$ is the covariance of variables $a_i$ and $a_j$, $\sigma_{a_i}$ is the standard deviation of $a_i$, and $\sigma_{a_j}$ is the standard deviation of $a_j$.

As mentioned above, public bicycle usage should be measured by a set of variables rather than a single variable. We conducted bivariate Pearson correlation analysis. We thus used multivariate analysis and multiple linear regression to analyse how the considered variables affect public bicycle trip production for different land uses. In statistics, linear regression is a system used to describe the relationship between the dependent variable and two or more explanatory independent variables (Abdpour, Younessi-Hmazekhanlu, & Ramazani, 2019). Multiple linear regression is one of the simplest and most intuitive methods to determine the effect of explanatory independent variables on the dependent variable (Deng, Fannon, & Eckelman, 2018) and has been used extensively in practical applications (Yan & Su, 2009). The explanatory independent variables we chose are public bicycle infrastructure, public transportation infrastructure, road characteristics, and the built environment. The dependent variable, hourly trip production for each bicycle station, is introduced as:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$$

(4)

where $Y$ is the hourly trips produced for each bicycle station, $x_k$ ($k=1, 2, 3, \ldots$) is the independent variables shown in Table 1 and the temporal variation mentioned above, $\beta_k$ ($k=1, 2, 3, \ldots$) is the coefficients of each of the independent variables, and $\beta_0$ is a constant parameter.

To validate the results, we used the mean absolute error (MAE), which is widely utilised for validating regression model results. The equation for MAE is:

$$MAE = \frac{\sum_{i=1}^{n} |y_i - Y_i|}{n}$$

(5)

where $y_i$ is the prediction and $Y_i$ is the true value.

### 3. RESULTS AND DISCUSSION

Both of the methods we used were conducted separately for different land uses, namely industrial, educational, residential, and commercial areas in Xiasha District. We first described public bicycle trip production for different land uses and then calculated Pearson correlation coefficients to explore possible bivariate correlations between the independent variables and the dependent variable for each land use. Finally, we conducted multivariate analysis with multiple linear regression to elucidate the relationships of independent variables with public bicycle trip productions for each land use.

#### 3.1 Exploratory analysis

Figure 3 shows public bicycle trip production for different land uses. Bicycle trip production for residential areas is similar for weekdays and the weekend. Moreover, public bicycles are frequently used in the mornings and in the evening peak times for residential and industrial areas. However, for industrial areas, bicycle utilization is low on the weekend. For educational areas, bicycle trip production is high during the day on weekdays and the
weekend. It is also high in commercial areas but is steadier throughout the
days of the week.

![Figure 4](image)

**Figure 4.** Public bicycle trip production for different land uses

### 3.2 Pearson correlation analysis

We used two approaches to achieve the objective of this study. First, to
explore the relationship between each independent variable and public
bicycle trip production, we conducted Pearson correlation analyses. The
independent variables in the analysis were the number of bicycle stations
within a 500m buffer, the number of bus stops within a 500m buffer, the
number of intersections within a 500m buffer, length of the roads (in
kilometres) within a 500m buffer, length of bicycle routes (in kilometres)
within a 500-m buffer, the distance to the nearest bus stop (in metres),
diversity, and density. *Table 3* shows the Pearson correlation coefficients.
Most of the independent variables were found to be positively associated
with trip production, with the exception of distance to the nearest bus stop.
The number of bus stops within a 500m buffer was associated with trip
production in industrial land use areas but not with trip production in other
land use areas. The length of bicycle routes within a 500m buffer and
distance to the nearest bus stop were not found to be associated with trip
production in residential land use areas. Moreover, none of the variables
were associated with trip production in commercial land use areas. Therefore,
the relationship between the variables for commercial land is not
considered in the remainder of the paper.

*Table 3* shows Pearson correlation coefficients between the variables and trip production for each
land use.

|                          | Educational land uses | Residential land uses | Industrial land uses | Commercial land uses |
|--------------------------|-----------------------|-----------------------|----------------------|----------------------|
| Number of bicycle stations within a 500m buffer | 0.12** | 0.16** | 0.1** | -0.16 |
| Number of bus stops within a 500m buffer | 0.48 | 0.00 | 0.16** | 0.03 |
| Number of intersections within a 500m buffer | 0.15** | 0.09* | 0.15** | 0.04 |
| Length of roads (in km) within a 500m buffer | 0.11** | 0.09* | 0.24** | -0.12 |
| Length of bicycle routes (in km) within a 500m buffer | 0.08* | 0.01 | 0.23** | -0.15 |
km) within a 500m buffer
Distance to the nearest bus stop (in meters) -0.16** -0.01 -0.1** 0.15
Diversity 0.06 -0.21** -2** 0.09
Density 0.7 0.2** 0.33** -0.15

** Significant at the 95% level.
* Significant at the 90% level.

3.3 Multiple linear regression

Second, we conducted multivariate analysis using multiple linear regression to analyse how the variables affect public bicycle trip production for different land uses. The independent variables for multiple linear regression are temporal variation (AM (07:00 - 09:00), Midday (09:00 - 12:00), PM (12:00 - 16:00), Evening (16:00 – 20:00), Weekdays, and Weekend), the number of bicycle stations within a 500m buffer, the number of bus stops within a 500m buffer, the number of intersections within a 500m buffer, the length of roads (in kilometres) within a 500m buffer, the length of bicycle routes (in kilometres) within a 500m buffer, the distance to the nearest bus stop (in meters), diversity, and density. Before conducting multiple linear regression, we used descriptive statistics to find outliers in the hourly bicycle trip data. Outputs that differed from the average by more than two standard deviations were considered outliers and were not considered for further analysis. Table 4 presents the multiple linear regression results. According to Durbin-Watson statistics in the table, the results show no multicollinearity among the independent variables for all the land uses. The R-squared value was low, but as our purpose is not predicting but explaining the variables that contribute to public bicycle trip production, this statistic is not an important value in this study.

Temporal indicators were found to be significantly associated with bicycle trip production in residential and industrial land use areas, especially during rush hours (07:00 - 09:00 and 16:00 - 20:00). That may be because during rush hours, people in residential and industrial land use areas are more likely to commute to or from work. These findings are consistent with the results of previous studies such as that by Wang, K., Akar, and Chen (2018). It is also clear that public bicycles were used more frequently during the 07:00 - 09:00 period relative to the 16:00 - 20:00 period, which is in contrast with the results of Faghih-Imani et al. (2014). However, there were no significant variables for trip production in educational land use areas (except on weekdays and the weekend). This may be because university students are living on campus and tend to have more flexible schedules across a day. Lecturers in universities also tend to not have a fixed time at which their workdays end. Therefore, the temporal variations are not significantly associated with trip production in educational land use areas. As emphasized by the positive coefficients for the weekday variable, people tend to ride more on weekdays. This finding corresponds with people’s travel patterns and is consistent with that of Faghih-Imani et al. (2014).

Public bicycle and bus facilities are important for bicycle usage (Akar & Clifton, 2009). The number of bicycle stations within a 500m buffer was found to be a statistically significant variable for trip productions for two types of land use: the number of bicycle stations was positively related to public bicycle trip production in educational land use areas but negatively related in industrial land use areas. This may be because the road environment in industrial areas is not friendly to cyclists. Increasing the
number of bicycle stations in educational land use areas would increase the number of bicycle trips. These findings are consistent with that of Faghih-Imani et al. (2014).

The number of bus stops within a 500m buffer was a statistically significant variable for trip production in all three land uses. Moreover, the number of bus stops within a 500m buffer was negatively related to trip production in educational and residential land use areas. These findings are in contrast with the results of most studies (Faghih-Imani & Eluru, 2016; Noland, Smart, & Guo, 2016). This may be because in educational and residential land use areas, if it is convenient to get to bus stops (more bus stops, more convenient locations), there is no need to use the public bicycle sharing system.

The road characteristics are regarded as important variables of bicycle trip production. In our study, the number of interactions within a 500m buffer was a statistically significant variable for residential and industrial land use areas. However, the length of bicycle routes within a 500m buffer was found to be significantly associated with bicycle trip production in residential land use areas. The length of roads within a 500m buffer was found to be positively associated with public bicycle trip production in educational land use areas because they are bicycle-friendly. More roadways would result in the production of more bicycle trips. Moreover, the distance to the nearest bus stop was also negatively associated with trip production for the three land uses, which is in contrast to the findings of Noland, Smart, and Guo (2016). This may be due to the same situation as with the number of bus stops within a 500m buffer. That is, if it is convenient to get to bus stops (proximity to bus stops), there is no need to use the public bicycle sharing system.

The built environment is a significant determinant for travel. Diversity was found to be a significant variable and positively associated with bicycle trip production in educational and industrial land use areas. Density was also found to be a significant variable and positively affected bicycle trip production in residential and industrial land use areas. Moreover, the MAE values shown in Table 4 indicate that the regression results are valid, especially the results for industrial land use areas.

Table 4. The results of multiple linear regression for different land use areas.

|                      | Educational land use | Residential land use | Industrial land use |
|----------------------|----------------------|----------------------|---------------------|
|                      | Coeff. | Sig.  | Coeff. | Sig.  | Coeff. | Sig.  |
| 07:00-09:00          | 0.65   | 0.517 | 2.69** | 0.007 | 6.56** | 0.000 |
| 09:00-12:00          | -1.89* | 0.058 | -1.71* | 0.088 | 0.11   | 0.912 |
| 16:00-20:00          | -1.3   | 0.194 | 2.23** | 0.026 | 4.83** | 0.000 |
| Weekday              | 3.76** | 0.000 | 4.42** | 0.000 | 6.56** | 0.000 |
| Number of bicycle    | 3.72** | 0.000 | -1.561 | 0.119 | -2.93** | 0.03  |
| stations within a    |         |       |        |       |        |       |
| 500m buffer          |         |       |        |       |        |       |
| Number of bus stops  | -3.27** | 0.001 | -2.07** | 0.039 | -0.301 | 0.763 |
| within a 500m buffer |         |       |        |       |        |       |
| Number of           | 1.1     | 0.272 | 2.67** | 0.008 | 3.603** | 0.000 |
| intersections       |         |       |        |       |        |       |
| within a 500m buffer |         |       |        |       |        |       |
| Length of roads      | 3.39** | 0.001 | 0.149  | 0.881 | -1.043 | 0.297 |
| (in km) within a 500m buffer | | | | | | |
| Length of bicycle    | 0.96    | 0.338 | -3.25** | 0.001 | -0.217 | 0.829 |
| routes (in km)       |         |       |        |       |        |       |
| within a 500m buffer |         |       |        |       |        |       |
buffer Distance to the nearest bus stop (meters) -4.56** 0.000 -1.77* 0.077 -2.01** 0.045
Diversity 1.89* 0.059 -0.921 0.358 2.49** 0.013
Density 0.21 0.833 2.85** 0.005 7.56** 0.000
Durbin-Watson 1.79 1.59 1.78
R² 0.15 0.16 0.21
MAE 3.44 3.13 2.6
** Significant at the 95% level.
* Significant at the 90% level.

The results could help planners better understand how to plan public bicycle stations and increase the use of public bicycles, which could improve sustainable urban development. Based on the study results, there should be different planning strategies for different land uses. For example, for educational land use, the number of bicycle stations, road length, and diversity should probably be increased, and the number of bus stops should probably be limited. For residential land use, the road conditions and density should probably be improved. The diversity and density should probably be increased in industrial land use areas. Further, the road environment could be improved to increase public bicycle usage.

4. CONCLUSIONS

The use of public bicycle sharing systems has greatly improved travel conditions and can also inhibit the excessive use of motor vehicles. The phenomenon is of great significance to sustainable urban development. As an emerging form of public transport, public bicycles have brought great convenience to travel and solved the problem of the 'last mile' at the end of travel. It is necessary to explain the variables that contribute to public bicycle trip production at the bicycle station level. The results can help us to better understand and better plan for public bicycle stations.

The exploratory analysis revealed that trip production behaviour is different for different land uses. We then conducted Pearson correlation analyses to explore the relationship between variables and bicycle trip production in different land uses. As none of the variables were associated with trip production for commercial land use area, we excluded this land use from the study. We then analysed how road characteristics affect public bicycle trip production for different land uses (educational, residential, and industrial land uses) using multiple linear regression modelling. The results show that various variables influence the use of public bicycles for these three land uses. They also confirm that for different land uses, the effects of temporal variables, public bicycle infrastructure, road characteristics, and public transportation facilities in the public bicycle system vary. According to the results of the multiple linear regression model, increasing the number of bicycle stations in educational land use areas would positively affect public bicycle trips. However, the temporal variations were not significantly associated with trip production in educational land use areas. The findings of this study will enable the identification of variables that can help to increase public bicycle usage in Hangzhou City and can result in recommendations about station size and location decisions. We also provide suggestions regarding how planning strategies can change based on the results. Further, our findings will be helpful for planners and engineers seeking to improve
the understanding of public bicycle trip production and sustainable urban development.

There are several limitations to this research. The population of a city and its areas is an important variable in public bicycle trip productions. However, population data are not included in this research because it is unavailable. There are also some unobserved factors not considered in the research. In a future study, we will use a random parameter model to overcome these limitations. Furthermore, dockless bicycle sharing systems are on the rise and may affect public bicycle sharing. Therefore, it is necessary to explore changes in public bicycle sharing systems after the implementation of dockless bicycles.

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