What Makes a City Bikeable? A Study of Intercity and Intracity Patterns of Bicycle Ridership using Mobike Big Data Records

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This paper examines how mass ridership data can help describe cities from the bikers' perspective. We explore the possibility of using the data to reveal general bikeability patterns in 202 major Chinese cities. This process is conducted by constructing a bikeability rating system, the Mobike Riding Index (MRI), to measure bikeability in terms of usage frequency and the built environment. We first investigated mass ridership data and relevant supporting data; we then established the MRI framework and calculated MRI scores accordingly. This study finds that people tend to ride shared bikes at speeds close to 10 km/h for an average distance of 2 km roughly three times a day. The MRI results show that at the street level, the weekday and weekend MRI distributions are analogous, with an average score of 49.8 (range 0–100). At the township level, high-scoring townships are those close to the city centre; at the city level, the MRI is unevenly distributed, with high-MRI cities along the southern coastline or in the middle inland area. These patterns have policy implications for urban planners and policy-makers. This is the first and largest-scale study to incorporate mobile bike-share data into bikeability measurements, thus laying the groundwork for further research.

Bikeability

Biking is beloved by a wide range of people for its environmental (Zhang and Mi, 2018) and physical health (Giles-Corti *et al*., 2010) benefits. Many cities worldwide started shared bike programmes years ago (DeMaio, 2009; Fishman *et al*., 2013; Shaheen *et al*., 2010; Si *et al*., 2019). However, it was only recently that shared bikes became 'smart' as a result of the development of information technology (Guo *et al*., 2017). These technological advancements, such as the implementation of anti-theft locks, GPS tracking, and mobile application-based user interfaces, have enabled a wider deployment of dockless shared bikes (Si *et al*., 2019). In the Chinese context, the bike-sharing market started to grow rapidly in 2016, with OFO, Mobike, Bluegogo and other similar start-ups entering the market. Driven by investments and growth, 20 million shared bikes were launched nationwide in just two years (Bi, 2018). These dockless bikes have several key merits: bike locations are searchable on mobile applications, users can return bikes anywhere anytime, and bike

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rentals are exceptionally cheap. Currently, in large Chinese cities such as Beijing, Shanghai, and Shenzhen, shared bikes are almost ubiquitous (figure 1). There is little product differentiation in shared bikes in terms of pricing and user experience. Registered users simply look for a bike offline or on the mobile application, select the ‘unlock’ option to scan the QR code marked on the bike, and start riding. The mobile application will record the trajectory and time for the rider. The typical cost of a rental is 1 RMB (US$0.15)/hour, or 10–20 RMB (US$1.5–3) per month. As a result of financial support, abundance, and the popularity of dockless shared bikes, publicly run bikes have been forced out of the market (Li *et al*., 2019).

Shared Bike Data Usage in Academia

Recently, academic interest in the bike-sharing system has increased, both inside and outside of China. The data derived from shared bikes are unprecedented. Bike companies collect enormous quantities of precise data about user travel time, trace, speed, and other user profile information. These data enable studies that could not have been conducted previously. In some studies, shared bike data are used to solve pressing social issues. He *et al*. (2018) developed a way to detect illegal parking using Mobike riding trajectories. Bao *et al*. (2017) used a data-driven method to propose bike lane plans using mass trajectory data. Others have developed spatiotemporal data analysis approaches to predict station demand (Ai *et al*., 2019; Guo *et al*., 2017; Li *et al*., 2019; Zhou, 2015).

In addition, many bike-sharing and bike infrastructure studies in the Western world focus on stationed bikes (Austwick *et al*., 2013; Carstensen *et al*., 2015). Reviews of dockless

Figure 1. The abundance of dockless bikes in Chinese cities (*Sources*: http://www.twoeggz.com/picture/696347.html; https://www.lianxianjia.com/zixun/140408.html)

shared bikes mainly focus on programmes in China and Singapore (Li *et al*., 2019; Xu *et al*., 2019). However, these studies focus on one or several cities, potentially lacking the ability to expand to other cities. No similar research examines bike-sharing programmes at the national level.

The Meaning of Bikeability

Bikeability initially branched off from the walkability measurement movement and has gained greater attention over the years (Porter *et al*., 2019). The term bikeability is commonly used in bike ridership and built environment studies; however, the factors that this term encompasses are often ambiguous. Some studies examine the suitability of built environments for biking (Mertens *et al*., 2017; Moudon *et al*., 2005; Orellana and Guerrero, 2019; Zhang *et al*., 2017). Others focus on perceived bikeability from a more subjective standpoint (Ferández-Heredia *et al*., 2014; Ma and Dill, 2017). Porter *et al*. (2019, p. 4) summarize the term 'bikeability' as being 'used to describe collective aspects of the environment that are conducive to bicycling'. Our bikeability definition stretches to include usage frequency, with the consideration that even though some streets may not have pleasant biking environments, they may attract many bikers due to their location or other factors.

As more people start to bike again, improving urban bikeability would benefit not only the riders but also the public as a whole. Nevertheless, the emphasis on bikeability is inadequate in Chinese cities compared to walkability (Gu *et al*., 2018). There is a need to study the bikeability of Chinese cities and propose practical ways to make streets safer and more appealing to bikers.

Mobike as Our Study Subject

The competition amongst bike-share providers is fierce. There were initially more than thirty companies in the market (ASKCI, 2018), but only Mobike, OFO, and Hellobike survived and took up the major market share in top-tier cities after two years of competition (Qianzhan, 2019). In November 2018, for example, the number of active users of Mobike, OFO and Hellobike was 19 million, 18 million and 7 million, respectively. However, OFO's market share was expected to drop after going bankrupt at the end of 2018 (Huang, 2018). In contrast, Mobike was acquired by an e-commerce giant, Meituan Dianping, and its status is secure at the moment. With the secured investment, Mobike was able to withdraw its 299 RMB (US$44.4) deposit charge, which attracted more users and hence is viewed as having promising market prospects. Moreover, Mobike bikes cover over 200 Chinese cities and across wide geographical regions. These traits are essential for our study, as we would like to explore general bike-riding patterns across China and be able to continue the study without considering bike ridership instability.

Our Study Aims

In this study, we explore the possibility of using Mobike's mass ridership data to study bike ridership in major cities across China. We divided our study into two parts. Part one conducts an in-depth examination of Mobike data to study ridership patterns. Part two constructs a bikeability rating system called the Mobike Riding Index (MRI), which reflects bikeability in terms of usage frequency and the built environment on a scale of 0 to 100. From the results of the MRI, we discuss the discernible patterns of the MRI at intercity and intracity scales. Our study focuses on the urban built-up area of 202 Chinese cities, which fills the gap of regional-scale bike data research. This paper contributes to the study of Chinese bikeability by being the first to create a bikeability rating index using massive bike data and the first to cross-sectionally study 202 cities. Its results would have implications for urban policymakers and inspire like-minded researchers.

Literature Review

Variables Used in Bikeability Measurements

Bikeability encompasses many different factors, and these factors are represented differently in different measurement approaches. The Copenhagenize Index (CI), the self-proclaimed most comprehensive worldwide ranking of bicycle-friendly cities, began in 2011 and incorporates thirteen parameters in its bikeability ranking methodology (Copenhagenize Design Co., 2019). It includes streetscape parameters (bicycle infrastructure, bicycle facilities, traffic calming), culture parameters (gender split, modal share for bicycles, modal share increase over the last 10 years, indicators of safety, image of the bicycle, cargo bikes), and ambition parameters (advocacy, politics, bike share); it also includes a bonus point to address any extra effort that is not reflected in these points. The consideration of bicycle facilities is in line with existing research. Rixey (2013) concludes that proximity and access to a comprehensive bike station network are critical to support ridership once demographic and built environment factors are controlled for. This index stands out amongst numerous bikeability measurements due to its expansive scale (Zayed, 2016). In the study of city readiness for cycling, Zayed chose case cities using the CI, indicating the credibility of the index's ranking in academia. Twelve variables were considered in Zayed's study, including city area, population and density, city form, city sector, land-use geography, road network length, motorized transport modal split, motorization rate, terrain slope, annual temperature, and yearly precipitation. Relevant research shows the importance of the variables used in this study. Zhang *et al*. (2017) find that factors including population density, bike lane length and diverse land-use types near bike parking places are positively associated with bike trip demand, whereas distance to the city centre is negatively associated with trip demand. In contrast to the CI, Zayed's study focuses more on city-related variables and natural conditions. Gu *et al*. (2018) created a street scoring framework for bikeability using eight parameters that covered three dimensions: a safety dimension (existence of bike lanes, existence of crossing facilities, bike lanes with illegal parking), a comfort dimension (streets with tree shade, bike lane isolation), and a convenience dimension (street network density, crossing facility density, facility accessibility). While CI parameters place more emphasis on social factors, Zayed's study focuses more on city-related figures, and Gu *et al*.'s index focuses mainly on the streets' built environment. Each rating system has a unique focus, while streets' built environment parameters are a common feature of each rating system.

Methods for the Evaluation of Bikeability

Next, we examine the methods that have been used in previous bikeability studies. The most straightforward approach would be point addition with equal weight, which is used in the CI. A similar approach is to compare parameters using statistical descriptive and factor analyses (Zayed, 2016). While weighting is not emphasized in these two approaches, Gu *et al*. (2018) used Shannon's information entropy weighting to reduce artificial effects in weighting and to avoid information overlap. However, since information entropy weighting is based on mathematical models instead of bikeability-related knowledge, it is difficult to justify the reliability of weighting. A regression model is used to forecast bike-sharing ridership. Rixey (2013) used factors including demographics, the built environment, the transportation network, and system-specified factors to explain the natural log of the number of rentals. Although this method is used for ridership forecasting, its result also reflects the degree of influence of different variables.

Scope of Study

Existing research varies in scope. It ranges from community to international levels. Community-level research provides an in-depth perspective in an area. Luo *et al*. (2018) studied the Qiaobei area of Nanjing to determine the influence of the built environment on public bike usage. Although the area is limited, the study implication is generalizable, as influential built environment factors such as bus stations and street amenities are common in other places. The most frequent level of study is the city. Studies have been conducted in Chinese cities (Ningbo, Zhongshan), North American cities (San Francisco, Chicago, Vancouver), and in an Ecuadorian city (Cuenca) (Ashqar *et al*., 2019; Gallop *et al*., 2011; Guo *et al*., 2017; Orellana and Guerrero, 2019; Zhang *et al*., 2017; Zhou, 2015). City-level studies, however, are harder to extrapolate due to their distinct culture, geographical location, and other factors. In addition, the built environment also varies widely from urban to suburban areas. Also common are multi-city/regional studies. The comparisons between different cities give another dimension to the study of bikeability. Research is mostly performed in the Western world, especially in the United States (Si *et al*., 2019). Chinese dockless shared bike schemes have not attracted sufficient research attention despite their size (Fishman, 2016; Si *et al*., 2019). At the international level, the CI is by far the most comprehensive (Copenhagenize Design Co, 2019; Zayed, 2016).

We will fill the gap in the existing literature by providing insights into shared bike ridership in the Chinese context and constructing a bikeability rating system using mass ridership data. Specifically, we will conduct a countrywide study covering major cities that had Mobike activities in September 2017. The data availability enables us to study ridership at different scales. This study encompasses trends from the regional level to the street level. Unlike existing literature that uses city administrative boundaries as the scope of study, we only consider urban built-up areas, making our study more urban-focused. This study is the first of its kind in the known literature and could have implications for researchers and urban practitioners.

Data and Methods

This study outlines several assumptions and hypotheses based on precedent studies. First, we expect to see more trips on weekdays than at weekends, as people use the dockless bike-sharing system more for commuting purposes (Li *et al*., 2019). We would also assume the overall trip frequency variations at weekends to be smaller and the temporal patterns across the city to be evenly distributed (Xu *et al*., 2019). Porter *et al*. (2019) also note that geographical location is an important factor that influences bikeability. It is particularly important in our research, since we are comparing cities across China, which spans a large latitude and longitude range. We would expect better bike ridership performance in the south, where the climate is more temperate. Since the information on user characteristics was not released, we assume it to be similar to that of the entire shared-bike industry in China. As shown by iiMedia Research (2008), a Chinese big-data consultantcy, out of all the shared bike users nationwide, males account for 4.4 per cent more than females. In terms of the age distribution, those younger than 24 years old account for the lowest proportion of users (only 4.8 per cent), and those aged 31–35 comprise the largest group of users (28.8 per cent). This group is followed by those aged 25–30 (25 per cent) and those aged 36–40 and older than 41 (each approximately 20 per cent). This distribution is generally even, so it is reasonable to assume that our MRI applies to the general population.

Mobike Data

One-week (4–10 September 2017) bike trip data at a national level were obtained from Mobike Inc. to conduct detailed research. This dataset originally covered the urban built-up area of 287 Chinese cities and 769,407 street segments and contains street ID, date, daily user volume, bike volume, speed, and other related parameters.

We conducted background research and checked the dataset's legitimacy. First, we assumed Mobike's market share to be consistent across different regions of China, since there is no precise measure of the difference. When this dataset was compiled in September 2017, Mobike and OFO were the two largest firms that shared the market almost evenly at the national level (CheetahGlobalLab, 2018). However, this dataset was set in a time frame that was close to the end of China's bike-share industry frenzy. Since the beginning of 2017, Mobike and OFO have been rapidly expanding both domestically and overseas (Zhou, 2017). However, in September both companies announced that they would stop launching new bikes in existing cities due to management difficulties (Cheng, 2017). In the meantime, dozens of similar firms shut down (CheetahGlobalLab, 2018). The shutdown wave drew shared bike users back to the biggest firms like Mobike and OFO, and hence, we assumed the dataset's representability of the larger bike user population.

Data Exploration

Since weekday and weekend travel patterns may be different, the Mobike data were divided into weekday and weekend datasets, and separate analyses were conducted. Data from 4 to 8 September were aggregated into a weekday dataset, and data from 9 and 10 September were aggregated into a weekend dataset. Table 1 lists the indicators after aggregation. These eight indicators have the same naming conventions, in which 1 denotes weekdays and 2 denotes weekends. Street ID and date were omitted as they were not included in the MRI framework.

The aggregated data were visualized in charts and maps. The Mobike data were geolocated on the map by joining them to the street network using ArcMap 10.5. Since Mobike had not opened its business in all 287 cities in China, streets in many of those inactive cities had zero bike counts. Therefore, a formula was used to select only valid cities. As shown in formula 1, the active city is defined as a

Table 1. Indicators for weekday and weekend datasets.

Indicators	*Definition*
UV1_SUM UV2_SUM	Cumulative user count on each street segment (1 for weekday, 2 for weekend)
UV1_MEAN UV2_ MEAN	Daily average user count on each street segment (1 for weekday, 2 for weekend)
PV1_SUM PV2_SUM	Cumulative unique trip count* on each street segment (1 for weekday, 2 for weekend)
PV1_ MEAN PV2_MEAN	Daily average trip count on each street segment (1 for weekday, 2 for weekend)
PV/UV1 PV/UV2	Daily average trip count per user on each street segment, or trip-to-user ratio (1 for weekday, 2 for weekend)
ORDCNT1 ORDCNT2	Daily average order count for users who passed the street segment (1 for weekday, 2 for weekend)
AVGDIS1 AVGDIS2	Daily average travel distance for users who passed the street segment (1 for weekday, 2 for weekend)
AVGSPD1 AVGSPD2	Daily average travel speed for users who passed the street segment (1 for weekday, 2 for weekend)

* 'Unique trip count' indicates that a street segment is only counted once in a trip order even if the user passes through it repeatedly.

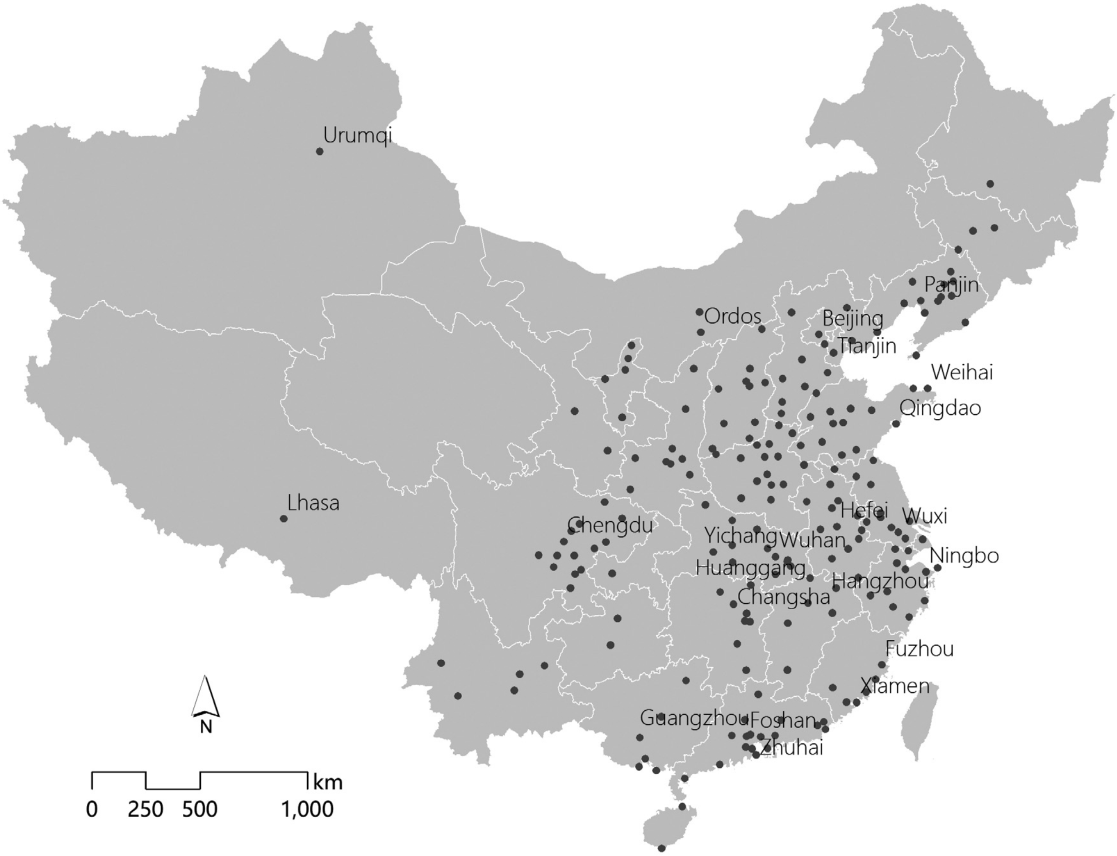


Figure 2. 202 active cities are preserved for further research.

city that has more than ten street segments for which cumulative trip counts are non-zero. With this criterion, 202 out of 287 cities, equivalent to 693,605 out of 769,407 street segments, were selected for further research. These 202 cities cover all major cities in China (figure 2), with a higher concentration in Eastern China.

$$\text{Active City} = \text{Number of Streets}_{((PV1\_SUM+PV2\_SUM)>0)} > 10 \quad \text{(formula 1)}$$

To further investigate the data, each indicator was visualized using a density chart. Since extreme values could highly skew the data distribution, the top and bottom 5 per cent of the dataset were removed. A density chart provides information similar to that presented in a histogram, but instead of plotting with columns, it plots a normal density curve. Essentially, a taller curve indicates the more frequent appearance of a number (R Core Team, 2013).

MRI Initial Framework

The Mobike Riding Index was created based on our understanding of bikeability and precedent studies. Bikeability should include two aspects: street usage frequency by bikers and built environment-related factors. The street usage is reflected by Mobike riding data, which show usage frequency and riding quantity. The built environment is further divided into the dimensions of street segment measurements and city environment. The street dimension includes measurements derived from the point of interest (function density and function mix) and other street characteristics, including junction density, street length, and width, which have been important in previous research (Gu *et al*., 2018; Zayed, 2016). Township-level population density is included, since it has been found to be relevant to high bikeability (Zhang *et al*., 2017). We also incorporated the Walk Score, a walkability measure we previously developed (Long *et al*., 2018), in the street dimension to indicate the convenience to a nearby point of interest (POI) and street amenities. In the city environment dimension, research has shown the importance to bikeability of city area, street length, weather, temperature, and household income (Guo *et al*., 2017; Porter *et al*., 2019; Zayed, 2016). These factors are reflected in our framework as the city centre area, number of street segments, total street length, annual average temperature, precipitation, city administrative level, and gross domestic product (GDP) per capita. This framework (figure 3) was reviewed by experts in related fields, including the Director of WRI Ross Center for Sustainable Cities and the Chief Data Scientist and CEO of Mobike Inc., who have years of practical knowledge in rider preferences. However, the MRI framework was later simplified to eleven factors due to various reasons addressed in the following two sub-sections.

Other Data

For the street measurements and city environment dimensions, we tried to obtain data for each proposed indicator, as shown in the MRI initial framework (figure 3). The datasets come from various sources, ranging from commercial data to manual collection. Table 2 presents the explanations and sources of all indicators from the street measurement and the city environment dimensions, respectively. With the available data, clarification is needed for the following terms: centre city, city's administrative core, road network and street amenities:

(*a*) The centre city refers to a city's largest concentrated urban built-up area within its administrative boundary (Long, 2016).

(*b*) The city's administrative core is used to represent the location of its local government, rather than the geometrical centroid, as cities usually expand radially from their local government.

Mobike Riding Data

1. User count per segment
2. Trip count per segment
3. Daily average user speed
4. Ratio between trip count and user count
5. Daily average user riding distance
6. Daily average user order count

Street Segment Measurements

1. Function density
2. Function mix
3. Junction density
4. Township level population density
5. Length
6. Width
7. Distance to city centre
8. Walk Score
9. Street greening
10. Street slope
11. Whether a street segment has a separated bike lane

City Environment

1. Annual GDP per capita
2. City administrative level
3. Average Annual Temperature
4. Annual average precipitation (mm)
5. City centre area (km^2)
6. Number of street segments
7. Total street segment length (m) in city centre

Figure 3. Initial MRI calculation framework.

(*c*) The road network refers to all simplified roads within the centre city boundary. Briefly, the original two-way roads were simplified into one, minor discontinuities were reconnected, and random branches were removed (Long, 2016).

(*d*) Finally, the street amenities, represented by the point of interest (POI), were obtained from a Chinese leading map company, which initially contained over twenty categories but was later generalized to nine, including restaurants, banks, and parks (Zhou and Long, 2017). However, street greening, street slope, separated bike lane, annual average precipitation, and annual temperature indicators were excluded due to insufficient data.

Data Correlation Analysis

To avoid overly correlated indicators in the MRI calculation process, the correlations for all indicators in each dimension are investigated. The Spearman rank correlation is used, as there is no pairwise linear relationship assumption between these indicators. As we expected, some indicators are highly correlated with each other; some are even perfectly correlated. It would be meaningless to include both. Thus, a benchmark of $\rho = 0.8$ is set to filter out the invalid indicators. The cut-off point is chosen such that only the perfectly associated indicator pairs are eliminated while the relatively highly correlated pairs are preserved. Correlation analysis pairs with

Table 2. List of street and city indicators and their definitions, calculation methods and sources.

Indicator	*Definition*	*Calculation Method*	*Source or Reference*
		Street Segment Measurement Indicators	
WALKSCORE	A rating system that reflects the walkability on a street segment, with a range of 0–100. The higher the score, the more likely it is that people walk on the street.	$\textit{Walk Score} = \sum_{i=1}^{n} (W_i \times f(S)) \times \frac{100}{15}$ W_i: An amenity's influential weight i: a type of amenity n: all types of amenities S: the distance from a type of amenity to the street in metres $f(S)$: the decay function of S	Long *et al.*, 2018
FUNCTION_DEN	Street segment function density	$\text{FUNCTION\_DEN} = \frac{\textit{number of POIs}}{\textit{area } (km^2)}$ POI: point of interests	Liu and Long, 2016
FUNCTION_MIX	Street segment function mix: the variety of amenity functions in an area	$\text{FUNCTION\_MIX} = -\sum_{i=1}^{n} (p_i \times \ln p_i)$ p_i: the ratio between a type of amenity and the total number of amenities that are along the street segment	Liu and Long, 2016
JUNCTION_DEN	Street segment junction density: the number of junctions in an area, unit: #/km^2	$\text{JUNCTION\_DEN} = \frac{\textit{number of junctions}}{\textit{0.5 km search radius}}$	The street network in the centre city is from a Chinese leading navigation company

Table 2 – *continued on page 64*

Table 2 – *continued from page 63*

Indicator	*Definition*	*Calculation Method*	*Source or Reference*
		Street Segment Measurement Indicators	
DIST_TO_CC	Street segment's distance (m) to the city's administrative core	Calculated the distance from a street segment's centroid to the city core using the spatial-join feature in ArcGIS	City's administrative core comes from manual identification.
STREET_LEN	Street segment length (m)	The default length in ArcGIS	
WIDTH	Street width (m)		Raw data
POP_DEN	The township-level population density (people/km^2)		The Sixth National Census (2010)
		City Environment Indicators	
STREET_COUNT	The number of street segments in the centre city	ArcGIS Summarize tool	
SUM_LEN	The total length (m) of street segments in the centre city	ArcGIS Summarize tool	
GDP_PC	The city's annual GDP per capita (RMB/person; based on the administrative boundary)		China City Statistical Yearbook (2015)
CITY_LEVEL_N	City levels: 1. Zhixiashi (ZXS), i.e. the direct-controlled municipality 2. Fushengji (FSJ), i.e., the sub-provincial city 3. Shenghui (SH), i.e. the provincial capital 4. Dijishi (DJS), i.e. the prefectural-level city		Long *et al*., 2018
AREA_CC	Area of the centre city (km^2)	The default polygon area in ArcGIS	

ρ>0.8 were treated by removing one of the pairs.

Data Transformation

Since some data are highly skewed and others have an inverse relationship with the MRI, a log transformation, normalization (formula 2) and reverse normalization (formula 3) were applied to counteract the negative effects of the original datasets. For example, the original street width ranges from 0 m to 130 m in the dataset. However, in theory, streets always have a width, and the zeros should be missing values. Therefore, replacing them with the average street width is a reasonable approach to handling these missing values. In addition, as Jacobs (1958) suggests, compared to wider streets, narrower streets are preferable for non-vehicular traffics. Thus, the street width was then reversed and normalized to reflect the reverse influence on the bikeability. Similarly, since distance to the city centre is inversely associated with bike trip demand (Zhang *et al*., 2017), it is also reversely scored. Table 3 lists all indicator manipulations. With the transformed indicators, we computed the sum by using equal weighting, which is a method used in the CI.

Normalization: $$\frac{(x_i - x_{min})}{(x_{max} - x_{min})} \qquad \text{(formula 2)}$$

Reverse normalization: $$1 - \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \qquad \text{(formula 3)}$$

Table 3. The list of data transformation methods for every indicator, including log transformation, conversion, and normalization.

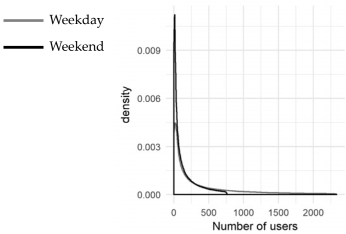
	Weight	*MRI Indicators*	*Performed Log Transformation*	*Conversions for Zeros and Unreasonable Values*	*Notes*
MRI Calculation	1/11	PV1_MEAN	Yes	0 to 0.01	
	1/11	PV2_MEAN	Yes	0 to 0.01	
	1/11	AVGSPD1	No	<0 to average speed	
	1/11	AVGSPD2	No	<0 to average speed	
	1/11	ORDCNT1	Yes	0 to 0.01	
	1/11	ORDCNT2	Yes	0 to 0.01	
	1/11	WALKSCORE	No		
	1/11	FUNCTION_DEN	Yes	0 to 0.01	
	1/11	JUNCTION_DEN	No		
	1/11	WIDTH	No	0 to average street width	Reverse scoring
	1/11	POP_DENSITY	Yes	0 to 0.1	
	1/11	DIST_TO_CC	Yes		Reverse scoring
	1/11	STREET_LEN	Yes		
	1/11	GDP_PC	No		

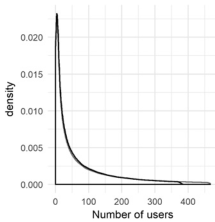
Results

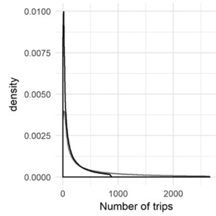
Mobike Data

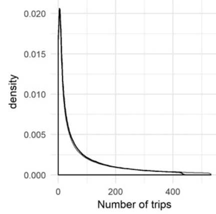
The in-depth exploration of Mobike data gives us a general sense of the differences and similarities in ridership patterns between weekdays and weekends. This information aids in the preparation of the construction of the MRI. As table 4 shows, the cumulative user count (UV_SUM) and cumulative trip count (PV_SUM) have similar distributions. Weekday (shown in a lighter colour) and weekend (shown in a lighter colour) distributions are skewed in opposite directions in both graphs. The cumulative user counts and trip counts for weekdays are much higher than those for weekends because there are five weekdays vs. only two weekend days. For the daily average, the daily average user count (UV_MEAN) and the daily average trip count (PV_MEAN) distributions both show that weekdays generate 13.5 per cent more trips and

Table 4. Density distributions of Mobike data (removing the top and bottom 5 per cent).

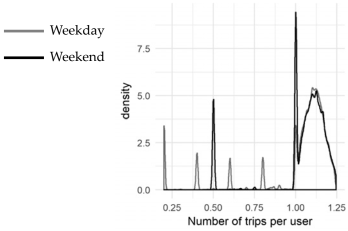


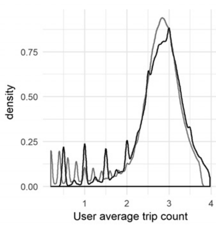


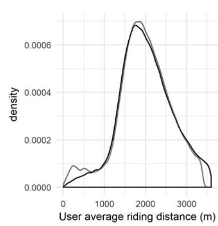


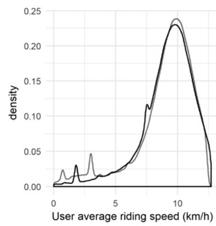


	UV_SUM		*UV_MEAN*		*PV_SUM*		*PV_MEAN*	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Average	388.3	136.7	77.7	68.4	439.9	154.9	88.0	77.5
Standard Deviation	518.5	172.0	103.7	86.0	590.2	196.1	118.0	98.0
Median	154.0	61.0	30.8	30.5	173.0	68.0	34.6	34.0
Maximum	2334.0	757.0	466.8	378.5	3253.0	865.0	650.6	432.5
Minimum	1.0	1.0	0.2	0.5	1.0	1.0	0.2	0.5









	PV/UV		*ORDCNT*		*AVGDIS*		*AVGSPD*	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Average	1.0	1.1	2.6	2.7	1959.0	2019.0	9.0	9.2
Standard Deviation	0.2	0.2	0.7	0.7	648.5	643.8	2.4	2.2

user counts than weekends. The average UV_MEAN for weekdays is 77.7, and for weekends, 68.4. Nevertheless, the travelling patterns for weekdays and weekends do not differ much in our finding, which is inconsistent with other findings that dockless bikes tend to have more influence on weekdays (Li *et al*., 2019). A possible explanation is that our data are aggregated daily not hourly, thus the temporal change is not obvious.

The average of the PV_MEAN for weekdays is 88.0, and for weekends, it is 77.5. The trip-to-user ratio density distribution shows that in most cases it equals one, but there are also incidents in which users have made more recurrent trips on the same day. For the trip-to-user ratio of less than one, there may have been data errors because it is impossible for a street segment to have more users than the number of trips. For instance, if a street segment has generated three trips, the maximum possible number of users should be three, and therefore, the trip-to-user ratio would never fall below 1. Fortunately, the average trip-to-user ratios are not skewed by the erroneous value, staying at 1.0 and 1.1 for weekday and weekend measures. The mean user order count (ORDCNT) peaks at approximately 3, with an average of 2.6 and 2.7 for weekdays and weekends, respectively. This finding implies that users, who generate trips on a street segment, ride Mobike bikes close to three times a day

Table 5. Spearman correlation matrices for Mobike dimension indicators (weekday | weekend) and street and city dimension indicators.

	AVGDIS	*AVGSPD*	*ORDCNT*	*PV/UV*	*PV_MEAN*	*PV_SUM*	*UV_SUM*	*UV_MEAN*
AVGDIS	1 | 1							
AVGSPD	0.83 | 0.81	1 | 1						
ORDCNT	0.64 | 0.65	0.69 | 0.69	1 | 1					
PV/UV	0.66 | 0.65	0.72 | 0.70	0.77 | 0.77	1 | 1				
PV_MEAN	0.67 | 0.67	0.74 | 0.72	0.74 | 0.75	**0.81 | 0.82**	1 | 1			
PV_SUM	0.67 | 0.67	0.74 | 0.72	0.74 | 0.75	**0.81 | 0.82**	**1 | 1**	1 | 1		
UV_SUM	0.67 | 0.67	0.74 | 0.72	0.74 | 0.74	**0.80 | 0.80**	**1 | 1**	**1 | 1**	1 | 1	
UV_MEAN	0.67 | 0.67	0.74 | 0.72	0.74 | 0.74	**0.80 | 0.80**	**1 | 1**	**1 | 1**	**1 | 1**	1 | 1

	FUNCTION_DEN	*FUNCTION_MIX*	*POP_DENSITY*	*WALK-DEN*	*JUNCTION_DEN*	*WIDTH DEN*	*STREET_LEN*	*DIST_TO_CC*
FUNCTION_DEN	1							
FUNCTION_MIX	**0.84**	1						
POP_DENSITY	0.3	0.28	1					
WALKSCORE	0.62	0.58	0.44	1				
JUNCTION_DEN	0.42	0.32	0.35	0.61	1			
WIDTH	0.06	0.05	–0.03	0.01	–0.03	1		
STREET_LEN	–0.21	0.02	–0.11	–0.19	–0.38	–0.03	1	
DIST_TO_CC	–0.32	–0.3	–0.3	–0.41	–0.24	0.02	0.08	1

	AREA_CC	*STREET_COUNT*	*SUM_LEN*	*GDP_PC*
AREA_CC	1			
STREET_COUNT	**0.91**	1		
SUM_LEN	**0.97**	**0.98**	1	
GDP_PC	0.49	0.56	0.53	1

* Bolded values indicate correlation coefficient >0.80.

on average, which could indicate that users use shared bikes as a connection from their homes to public transportation. The mean user distance distribution indicates that the most common riding distance is approximately 2,000 m, with slightly less on weekdays (1,959 m) and more at weekends (2,019 m). Finally, the mean user speed distribution shows that the most frequent riding speed is approximately 10 km/h; the average is 9 km/h for weekdays and 9.2 km/h for weekends.

Correlation Result and Finalized MRI Framework

The correlation test is used to determine the association between the indicators we plan to consider. Table 5 shows the correlation matrices for all indicators divided by dimensions. For the Mobike dimension, weekday and weekend results are shown side by side. Their values are highly analogous. The trip count (PV_MEAN and PV_SUM) and user count (UV_MEAN and UV_SUM) variables have almost perfect correlations and hence are excluded. After using the benchmark, only the indicators PV_MEAN, AVGSPD, and ORDCNT were kept in the Mobike dimension.

For the street dimension, the correlation between the street function mix and the street function density is 0.84, which is beyond our benchmark. Thus, only one of them could be kept in the MRI framework. Looking at the correlation plot, FUNCTION_MIX is less correlated with other indicators compared with FUNCTION_DEN, making it the better one to remove. In addition, as mentioned earlier, street greening, street slope, and whether a street segment has a separated bike lane were removed due to insufficient data. As a result, only the function density, junction density, population density, street length, street width, distance to city administrative core, and Walk Score were kept in the street dimension.

In the city environment dimension, many indicators were omitted due to various issues. AREA_CC, STREET_COUNT, and SUM_LEN were removed due to high correlation, and the city administrative level was withdrawn as it is unclear how the city level can influence ridership. As a result, this city environment dimension contains only the city's annual GDP per capita.

The final framework is shown in figure 4,

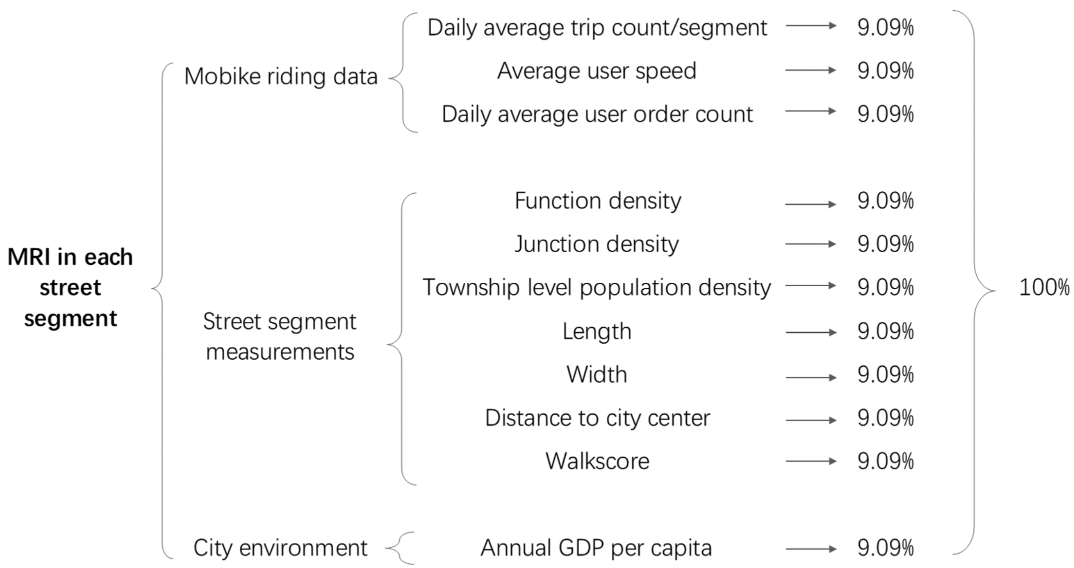


Figure 4. The finalized MRI calculation formula contains eleven equally weighted indicators from three dimensions.

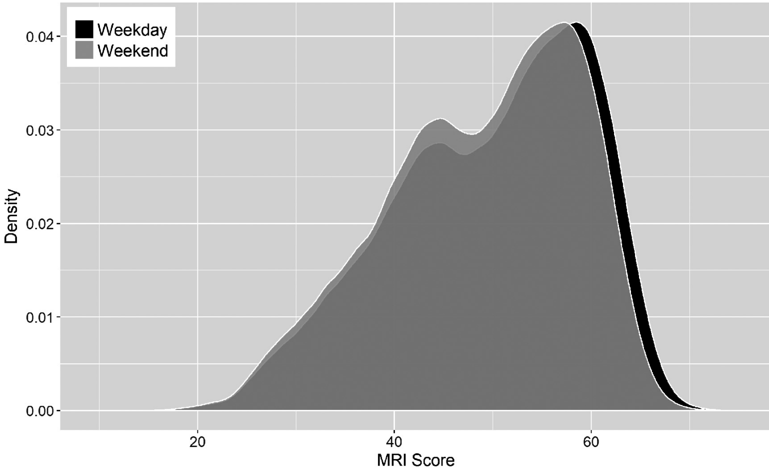


Figure 5. The distributions of MRI scores for weekdays and weekends.

which contains three dimensions and eleven equally weighted indicators summing up to the final MRI, a 0–100 scoring system. This scoring system is used as a basis for our evaluation of nationwide bikeability.

MRI Results

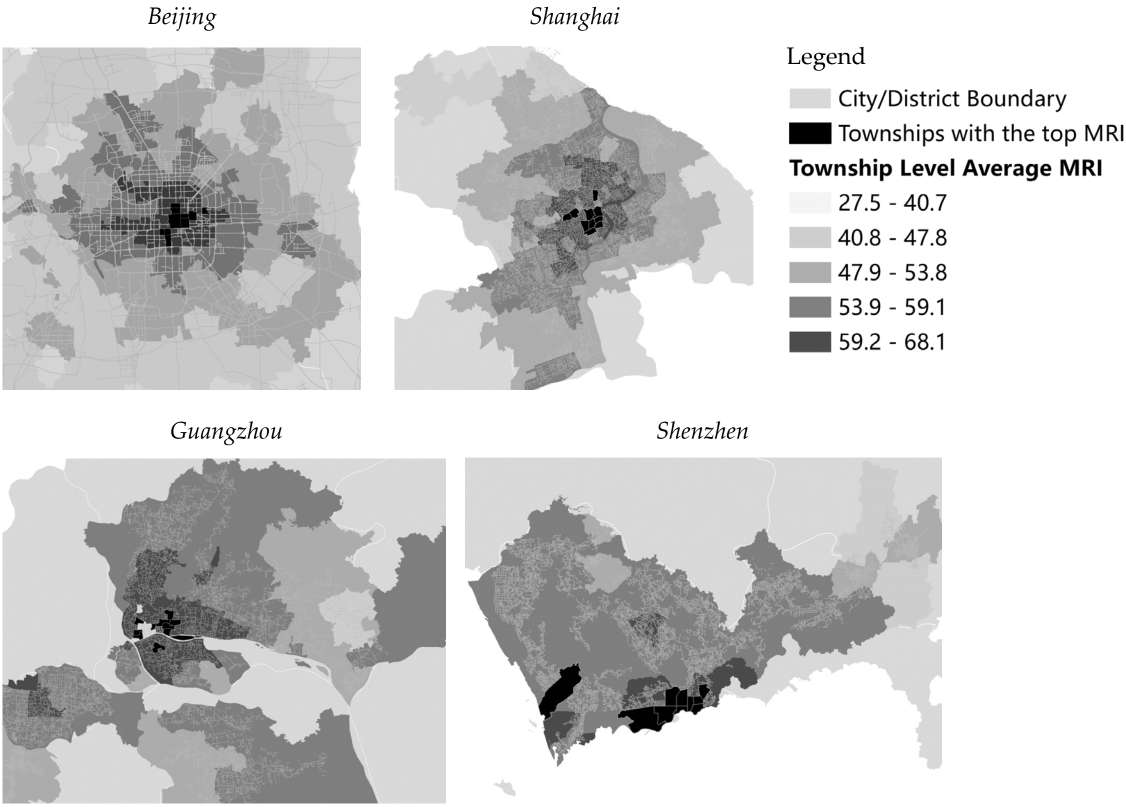
The MRI scores for both weekdays and weekends are visualized in figure 5. The weekday MRI ranges from 9.3 to 75.1, with an average of 49.8, whereas the weekend MRI ranges from 9.3 to 73.7, averaging 48.8. Although the weekday MRI scores are slightly higher than the weekend ones, their distributions almost overlap each other. This is not unexpected given that the Mobike daily trip counts and user counts are very similar (table 4). Therefore, it is reasonable to assume that by analysing either indicator, the result would be similar to its counterpart. The following results mainly focus on the weekday scores.

The interpretation of MRI results can be divided into three levels. First, at the street level, the nationwide MRI ranges from 9.3 to 75.1, with an average of 49.8 out of 100. The overall score has room for improvement. On the township level, high-MRI townships tend to cluster in city centres, given that the top MRI townships are in four megacities (table 6). Taking Beijing as an example, nine out of ten townships are in Beijing historic districts, with only one towards the East in a business district. Similarly, the top MRI townships in Shanghai are concentrated in the historic districts, i.e. Huangpu and Jing'an. Shenzhen has an outlier in the west, where new development is occurring. This finding broadens the finding of Gu *et al*. (2018): not only do city centres tend to have higher walkability than city peripherals, but they also have higher bikeability. This finding is not difficult to imagine because the central area usually has more people, shorter street segments, and higher function density and diversity, which all positively contribute to higher MRIs. Lastly, at the city level, high-MRI cities are widely spread throughout mainland China (figure 6). The cities with the largest circles are along the southern coastline and around Chengdu and Wuhan, where cities are also more clustered. In contrast, northern cities are comparatively weaker in MRI ratings, especially in the cities above Hefei, which are shown in small dots. However, a low MRI may not rule out these cities' bikeability, as there may still be many private bike users, or there is simply no demand for bike trips. To better understand these factors, field trips and onsite observations are needed.

Discussion

This study is considered to be the first bike-

Table 6. Top-ten townships (shown in black) in four Chinese megacities.



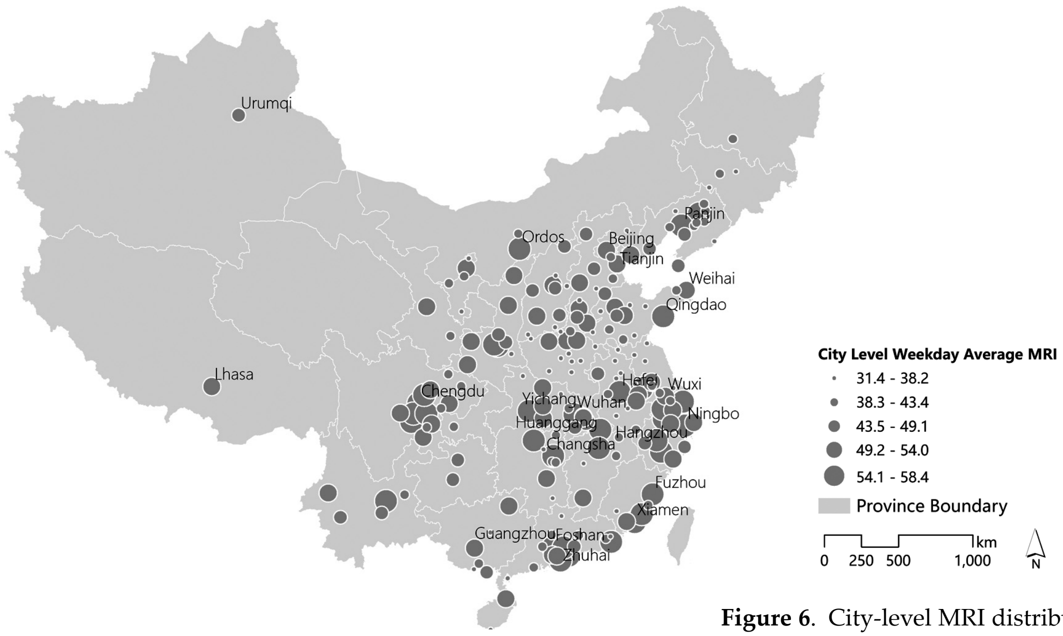


Figure 6. City-level MRI distribution.

ability rating system using mobile bike-share data in China, given that Porter *et al*. (2019) state that well-established research has not been published on the bikeability index in regions outside of North America. Our study incorporates 202 cities in China, the size of which is unprecedented for bikeability studies. In most studies, only a handful of cities are studied (Du and Cheng, 2018; Mattson and Godavarthy, 2017).

MRI as a Bikeability Measurement

Compared to existing measurements, the MRI carries several merits. First, the use of bike-share data directly reflects a street's usefulness to bike users. This dimension has not been used in previous bikeability studies. Second, other supporting data are a mixture of traditional and new datasets, such as the *China City Statistical Yearbook* (traditional), the nationwide road network (new) and point of interest (new). Third, the wide availability of the MRI enables cross-sectional analysis among a large number of cities. Under the rapid evolution of shared bikes worldwide, this kind of evaluation is needed for understanding challenges in sustainable development (Si *et al*., 2019).

This framework is intended to function as a preliminary framework that lays the groundwork for more sophisticated studies in the future. However, several aspects need improvement. The current Mobike data are provided on a daily basis rather than on an hourly basis; thus, this measurement prevents us from conducting a more detailed rating. Moreover, these Mobike data do not include information on user characteristics, so we had to use external research to assume the user characteristics, for example, the gender ratio and market share conducted by iiMedia. The representativeness of our finding could have been better studied had information on user characteristics been available. This improvement would rely on closer collaboration with Mobike Inc. or similar organizations. Moreover, the framework had to compromise the number of indicators due to the absence of data for annual temperature, precipitation and other factors, despite the influence of weather on bikeability (Gallop *et al*., 2011). More data-mining efforts are required.

There are several potential uses of the MRI. For map navigation providers, the MRI can help navigation companies recommend better routes to bike riders. For shared bike providers, this evaluation can help clarify the demand and supply relationship. For shared bike management teams, this pattern may indicate the need for the allocation of more employees to city centres to provide sufficient bike parking maintenance and supply.

Practical Implications

Mobike data reveal common biking behaviours that can inform biking-related policymaking. We found that Mobike users across major cities in China tend to ride at a speed of approximately 10 km/h, a distance of approximately 2 km per trip, and a frequency of close to three times a day. Several studies have raised concern that the shortage of biking infrastructure and corresponding laws have threatened users' health and safety (Si *et al*., 2019). These travel habits are hence crucial forms of information for urban planners, as this information can allow them to better facilitate and regulate bike trips in cities. The bike infrastructure should be designed to accommodate riders' speed. For example, the bike speed limit can be a multiple of the common riding speed; the bike lane protecting barricade can be designed to best protect normal-speed riders. Planners should also keep in mind the coverage of public transit so that riders can get to transit stops within a 2-km bike trip. On average, Mobike users use shared bikes almost three times a day, suggesting that riding shared bikes is becoming an essential part of their daily transit routine. Thus, providing a better biking environment will benefit a large number of shared bike users and potentially draw more people into biking.

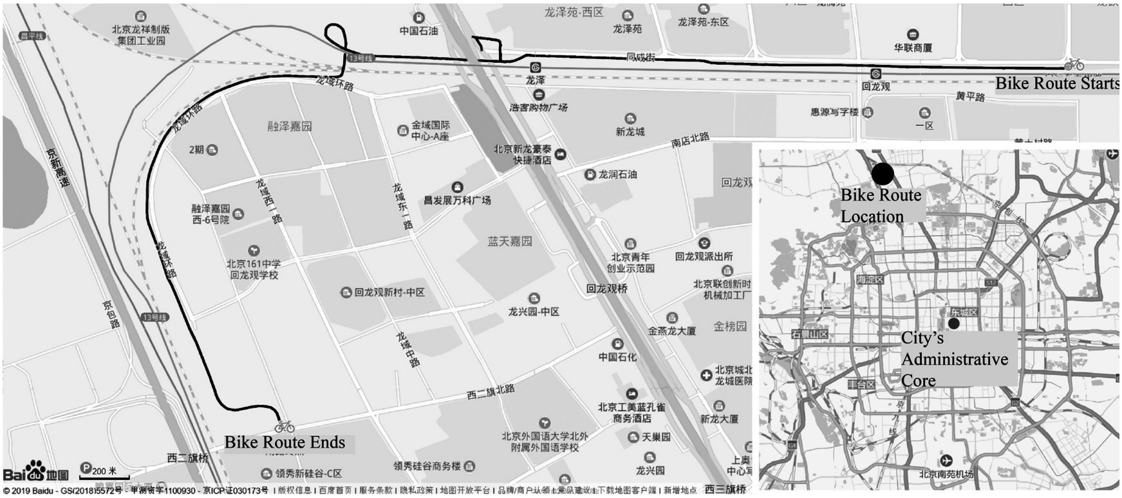


Figure 7. Beijing's first bike-exclusive route and its location with reference to Beijing city.

It would be interesting to test these findings and implications in practical settings. Recently, Beijing opened its first bike-only route in Changping District, a northern suburb (Du, 2019), with the intention of alleviating public transit and vehicular traffic. Shown as a green line in figure 7, this bike route is a 6.5-km path connecting a large residential community (labelled 'Bike Route Starts') and an IT hub ('Bike Route Ends'). Based on our finding that most trips are concentrated in city centres and that the average length of travel is one-third of the route, we may not expect to see overwhelming usage of this route. However, its actual usage is subject to observation.

At the city level, the highest MRI cities are distributed widely (cities with larger circles shown in figure 6), covering the Yangtze River Delta, the Pearl River Delta, and the inland area. However, better-performing cities tend to cluster in southern cities, divided by the Yangtze River. For policy-makers, knowing each city's MRI will allow them to release more targeted policies and provide tailored support to different cities. For cities with high MRI, the focus would be on how to manage shared bike parking effectively and ensure sufficient bike supply for areas with high demand. For cities with lower MRI, the policy focus should be to determine the reasons for the low scores by conducting case-by-case studies. If bike demand exists, then planners need to seek ways to improve bikeability.

Future Directions

This research has its limitations but can be converted into next-stage research plans. Currently it lacks temporal analyses. Temporal studies are important to determine rider behaviours depending on the granularity of the data. For example, hourly data are useful in studying the differences and similarities in riding patterns across China, whereas monthly data or daily data with a longer time period would help uncover seasonal changes in Chinese bikers' behaviours and how they differ in different regions. These objectives may require further collaboration with bike-share companies or self-collected data.

Future research would include the creation of a dynamic MRI and the application of different weights to different indicators. Ideally, the MRI should be frequently updated. The city environment dimension should be updated yearly, the street dimension monthly, and Mobike data daily, thus providing people with navigation suggestions dynamically. The next step is to apply appropriate weights to the indicators based on further research and bikers' feedback. The MRI framework is currently weighted equally. Although it may not reflect reality, we are hesitant to arbitrarily provide an unequal weight to any indicator without solid research. Thus, we hope to allow the actual users to evaluate the accuracy of our ratings, and we can then adjust the ratings to better reflect reality. With the dynamically updated MRI and an established rating feedback loop, the MRI will become more accurate and practical.

Conclusion

Against the backdrop of the booming dockless bike-share industry, we used Mobike riding data and other built environment parameters to study bikeability in China. We explored the possibility of finding a general pattern in biking behaviour across Chinese major cities. Our detailed analysis of week-long Mobike riding data from September 2017 reveals frequent travel speeds, travel counts and travel distances. We also constructed a riding index, the MRI, to study where the most bikeable areas are located.

As preliminary research, the findings have targeted implications for interested parties. For urban planners and government officials, the MRI result provides an approach to understanding riding conditions, opportunity, and constraints in different Chinese cities. For researchers, this research addresses the topic of bikeability calculations and aims to create a more accurate MRI. For citizens, the MRI helps them better understand their cities, neighbourhoods, and streets and hence optimize their travel routes. This area of research has strong potential for discussion as more data types become widely available.

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CONFLICT OF INTEREST

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

The authors contributed equally to this study and share the first authorship.

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