Research Paper

Research on regularity and influence of the spatiotemporal distribution on university shared bikes -- A case study of Tsinghua University

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Abstract

Shared bikes on university campuses is important due to the significant increase in usage conflicts in recent years. Existing studies either using subjective evaluations or black-box models, which lack objectivity and interpretability. This study uses the POI and streetscapes indicator to investigate the spatial distribution of shared bikes at university and gains a high R-squared value. The study ranks the most significant environmental factors contributing to shared bike usage conflicts, and found that the number of entrances, total road length, intersections consistently, and residential density have the greatest impact on shared bike usage conflicts. It suggests designing parking spots to relieve traffic conflicts and adjusting shared bike distribution in residential areas by replenishing bikes in dormitory areas during peak hours. These recommendations can help improve the efficiency of shared bike management on campus and alleviate usage conflicts. The methodology used in this study can also be applied in other small-scale scenarios to investigate the spatial distribution of shared bikes and their impact on the built environment. This study provides insights into the impact of shared bikes on the built environment but does not just call for increasing their numbers, which is of great relevance to policymakers, urban planners, and researchers.

Keywords

shared bike; built environment; spatial and temporal distribution patterns; campus design and planning; regulation strategy

1. Introduction

1.1 Conceptual of Dockless Bike Sharing System (DBSS)

In recent years, dockless bike sharing systems (DBSS), also known as free-floating bike sharing systems (Xu et al., 2019), have gained significant popularity in China. These systems offer users the autonomy and convenience of unlocking and paying for bikes through mobile apps, without the need for docking stations (He and Wang, 2023). They have effectively reduced reliance on private cars for short-distance travel (Qin and Karimi, 2023). Therefore, shared bikes have been recognized as a crucial solution for reducing carbon emissions, and their popularity is rapidly increasing (Zhao et al., 2023).

1.2 Conflicts on Campus Bike Sharing

Since the introduction of bike sharing in the Chinese market, students have been the primary users of shared bikes. Surveys indicate that the first platform-based shared bike service in China was launched on the campus of Peking University in 2014 (Chen et al., 2022). Students remain the largest customer segment for shared bikes (Kellstedt et al., 2019), with users under the age of 30 constituting 30% of the total customer base （CAICT, 2018）.

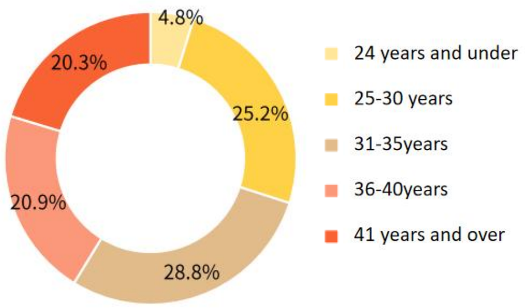

Figure 1. Age distribution of bike-sharing users in 2017. Source: iiMedia Polaris Internet Product Analysis System (bjx.iimedia.cn).

However, In universities, where land is limited, and buildings are older, the layout and deployment of shared bikes has become the most pressing issue for university management systems. Firstly, the current built environment often fails to cater to the specific needs of shared bike usage, and the changing needs of user various day by day (Chen et al., 2018), which raises concerns about whether campus areas can support the surge of shared bikes. Secondly, peak-hour bike shortages and improper parking, leading to the occupation of public areas within the campus (Chevalier et al., 2019) ,and this oversight has a negative impact on campus landscapes and increases the likelihood of accidents and traffic jams (Sun and Duan, 2021). Furthermore, as time passed, this problem become particularly severe in old campus settings where renovation opportunities and space are limited, yet shared bike usage conflicts are twice as severe as in urban areas. Therefore, the shared bikes on campuses remain inadequate but have led to severe traffic accidents, congestion, and usage conflicts.

1.3 Literature Review

To address the existing issues related to campus bike sharing, scholars both domestically and internationally have conducted preliminary discussions. However, existing research mainly relies on questionnaire data and subjective evaluation systems, lacking objectivity. Another approach involves constructing models, often referred to as "black box models," which only provide judgment on the conclusions but fail to explain the underlying principles and influencing factors. In recent years, scholars have proposed using Point of Interest (POI) and other indicators to predict the impact, but the effectiveness of such models in different scales, usage scenarios, and functional contexts still requires further examination (Chen and Ye, 2021).

The above review indicates that while bike sharing has been widely promoted, there is still a need to improve the reliability and interpretability of bike distribution patterns on university campuses (Godavarthy et al., 2022). The application of Geographically Weighted Regression (GWR) models may offer a solution to this problem. However, the effectiveness of such an approach in the context of university campuses with their unique functionalities requires further exploration (Zhou et al., 2023). Therefore, this study focuses on Tsinghua University, a typical Chinese university with shared bike usage, and aims to use the GWR model to investigate the spatial-temporal distribution patterns of shared bikes on campus. The study intends to provide constructive recommendations for optimizing the integration of shared bikes and the built environment on university campuses (Yang et al., 2017).

Scale	*Types*	*Author*	*research method*	*research result*
University	*Subjective evaluation*	TANG,Y. et al.,2019.	Questionnaires	Suggestions for optimising shared bicycle travel on campus
		TANG, M., et al.,2021.	Questionnaires, spatial syntax, Tyson polygons	A multi-level bicycle sharing parking system
		ZHENG, T. W et al., 2019.	Heat map overlaid with shared bike riding segments	Establishes a campus cycling safety evaluation index system
	Objective model	JIANG, X. et al., 2022.	Time series regression	A model for predicting the short-term supply and demand of dockless shared bicycles on campus
		SUN, Q, et al., 2022.	Non-negative Matrix Factorization(NMF)	A prediction model with better accuracy than BP neural network and LSTM neural network
City	*Subjective and objective modelling*	LI, H. et al., 2022.	The impact of junctions and POI) etc. on cycling demand	A prediction model with higher accuracy than least squares regression models and geographically weighted regression models
		XU, B & Lu, Q. 2023,	Impact of built environment and regional economic attributes on parking demand	A model with higher explanatory power than the spatio-temporal Geographical and Temporal Weighted Regression (GTWR) was obtained
		WEN, C. et al., 2022.	Bicycle data, POI, field survey and questionnaire collection	Propose a GMOD model to finalise the purpose of the user's trip

Table 1. Literature review on shared bikes model in different scales.

1.4 Research objectives

Therefore, this study focuses on exploring the most effective ways to improve the adaptation between the built environment and shared bike usage, and university campuses are the first to be explored. The study emphasizes the importance of considering the carrying capacity and usage patterns between the built environment and shared bikes and finding effective ways to invest in shared bikes. The study focuses to figure out these objects:

1) A model construction method that can be used for investigating small-scale shared bike usage pattern;

2) An assessment method for the adaptability of the built environment to shared bikes is proposed;

3) This study highlights new factors for improving the efficiency of shared bike usage.

2. Methodology

2.1 Study Area

The study area chosen for this research is Beijing, which has the highest number of universities in China, with a total of 87 universities. Among them, the Haidian District is the most densely populated area with universities, housing 35 universities. According to statistics from 2017, the monthly active user (MAU) count for bike-sharing in Beijing was approximately 4 million, accounting for 20.2% of the total national user base (Trustdata, 2018). As early as January 2016, bike-sharing platforms were already operational in Haidian District, covering six universities including Peking University, with over 5,000 bikes available. During peak periods, approximately 20,000 people were using the bikes daily (Gao et al., 2023). The abundance of users, mature development system, and large dataset at Tsinghua University, located in an area with the highest bike-sharing user count and earliest deployment, make it conducive to drawing reliable conclusions, which can serve as a reference for other universities.

2.2 Data Source

The original dataset used in this research is the Mobike Cup Algorithm Challenge Dataset from 2017, provided by Mobike. The report indicates that Mobike had the highest user coverage among bike-sharing companies nationwide (Trustdata, 2018). The dataset comprises 3,214,096 bike trip records in Beijing from May 10 to May 24, with seven data fields: Order ID, User ID, Vehicle ID, Vehicle Type, Ride Start Time, and Start and End Points of the trip. The start and end points are represented by 7-digit Geohash codes, each representing an area of approximately 152 m × 152 m. Python was used to decode the geospatial information.

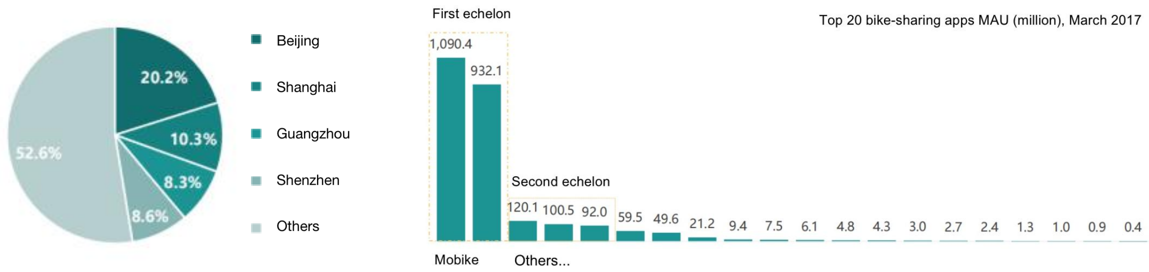

Figure 2. National share by city and bike-sharing MAU in 2017. Source: TRUSTDATA.

Order id	*User id*	*Bike id*	*biketype*	*starttime*	*geohashed_start_loc*	*geohashed_end_loc*
1893973	451147	210617	2	2017/5/14 22:16:50	wx4snhx	wx4snhj
4657992	1061133	465394	1	2017/5/14 22:16:52	wx4dr59	wx4dquz
2965085	549189	310572	1	2017/5/14 22:16:51	wx4fgur	wx4fu5n
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Table 2. Sample dataset for the 2017 Mobley Cup Algorithm Challenge. Source: Mobike.

2.3 Data Cleaning

To ensure data quality, the decoded data underwent a cleaning process to handle potential anomalies caused by weather conditions or software issues. Firstly, using Python, weather data for Haidian District from May 10 to May 24, 2017, was obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF), and only the records corresponding to sunny days were retained (Jaber and Csonka, 2023). Following the research method of Zhai et al., 537,385 records from May 11 and 12 were selected as weekday analysis data, and 461,876 records from May 13 and 14 were selected as weekend analysis data for comparison (Zhai, D. & Zhuo, J, 2021).

Next, the latitude and longitude of the bike-sharing origin-destination (OD) points were converted to X and Y coordinates in the Gauss-Krüger coordinate system using the Gauss projection (Xin et al., 2023). The Euclidean distance for each OD pair was calculated. The widely adopted box plot method in academia and industry was employed to eliminate outliers, removing orders with OD distances greater than the upper whisker of 1685.02 m for weekends and 1747.94 m for weekdays. This resulted in a selection of 433,327 records for weekends and 501,857 records for weekdays.

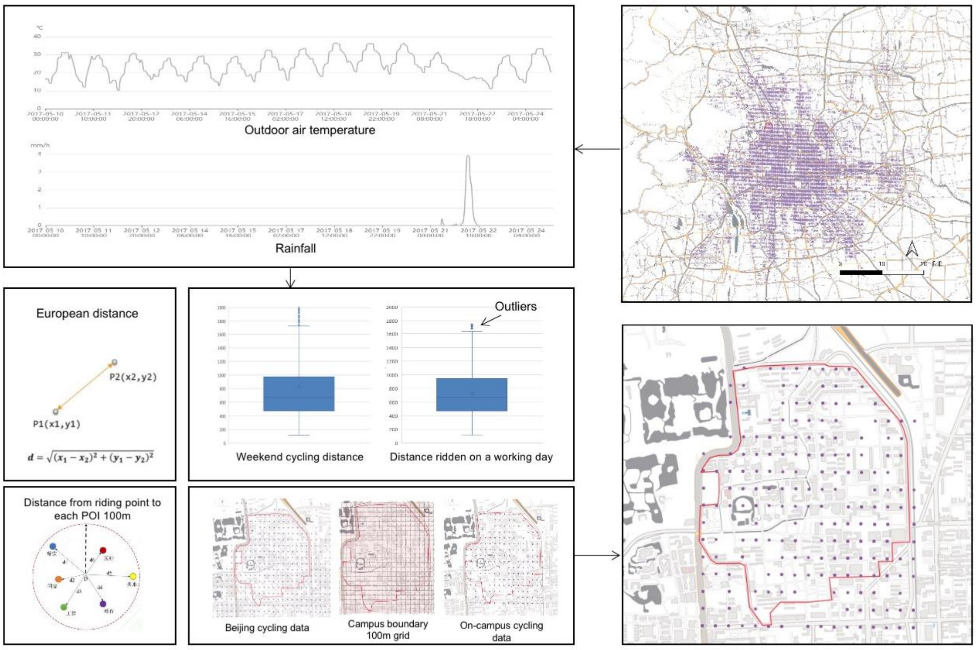

Figure 3. Dataset cleaning and cropping process.

Finally, using QGIS, the research area was delineated by clipping the coordinates of Tsinghua University. Since the Mobike dataset used GCJ02 coordinate system, it was converted to the WGS coordinate system for ease of subsequent processing. According to the findings of Wen et al. (Wen, C. et al, 2022), the maximum walking radius for riders was determined to be 100 m. Therefore, a research grid of 100 m × 100 m was established. The geographic boundary of Tsinghua University's campus was obtained from the Gaode Maps API to perform a secondary filtering of the data within the study area. Consequently, the final dataset consisted of 3,262 origin records and 2,969 destination records for weekdays, as well as 2,044 origin records and 1,967 destination records for weekends.

2.4 Description of Factors Influencing Bike Usage

Existing literature suggests that built environment factors influencing bike usage and parking demand include population density, land use, service facility density, road attributes, public transportation accessibility, and location conditions (Xu, B. & Lu, Q. 2023). Given the specific characteristics of university campuses, this research primarily focuses on service facility density and road attributes as the influencing factors. The data for service facility density and road attributes were obtained from the POI2017, Junction2014, Street2016, Road2016, and Streetscapes2016 datasets.

2.5 Research Flow

The research framework consists of two aspects: spatial distribution and temporal distribution. The spatial distribution includes the locations of bike trip origins and destinations for weekends and weekdays (Zhang et al., 2021). The temporal distribution involves selecting representative time periods by plotting the overall distribution of the data. For the analysis of influencing factors, based on a review of the literature, the dependent variables were identified as road attributes and service facility density. Additional street form indicators were included for auxiliary analysis. Pearson correlation coefficient analysis and R-squared prediction were used to identify factors with strong correlations(Liu and Lin, 2019). The selected factors, ranked according to their R-squared prediction values, were added to the multiple linear regression (MLR) model (Zhang et al., 2017). Variables with variance inflation factors (VIF) higher than 10 were excluded. The final MLR model can explain the impact and predictability of different built environment factors on bike parking and usage (Godavarthy et al., 2022).

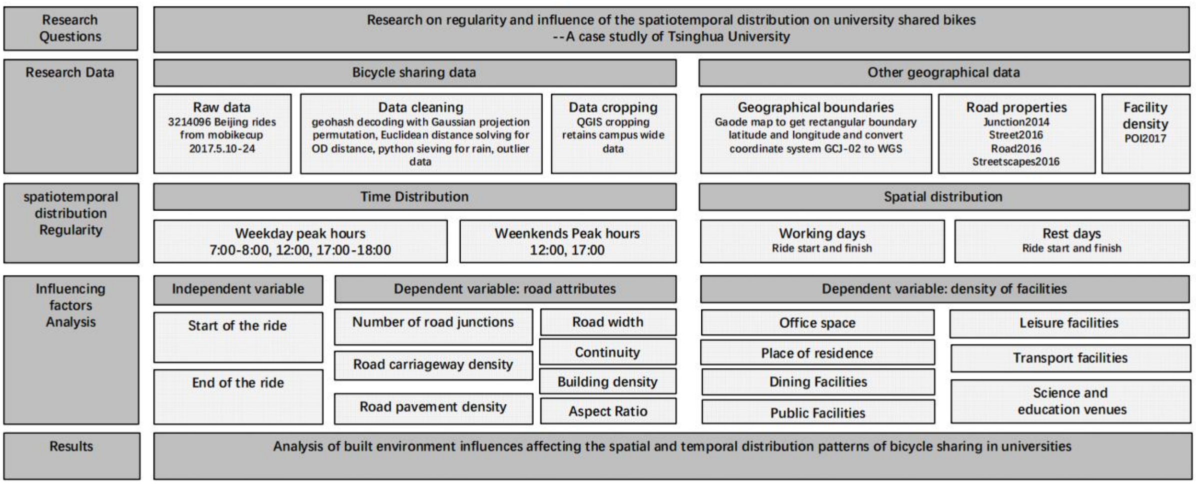

Figure 4. Research Flow.

3. Result and Discussion

3.1 Temporal Patterns of Bike Usage at University

The usage of shared bikes at Tsinghua University exhibits distinct temporal patterns between weekdays and weekends. Through analyzing the time-specific bike trip data within the campus, we found that the tidal effect of bike usage is more pronounced within the university premises. Specifically, during weekdays, in the campus, the peak usage quantity during certain time periods is 3 to 4 times higher than the normal usage periods. In contrast, the peak usage for bikes in urban is only twice as high as the normal usage periods. Additionally, there is a peak observed between 10:00 and 14:00 on weekdays in the campus. During weekends, there is also a peak observed within the campus, which is significantly different from the usage patterns in urban. Therefore, it can be concluded that the temporal patterns of bike usage are more pronounced within the university campus, indicating a stronger regularity and greater potential for optimization between shared bikes and the built environment.

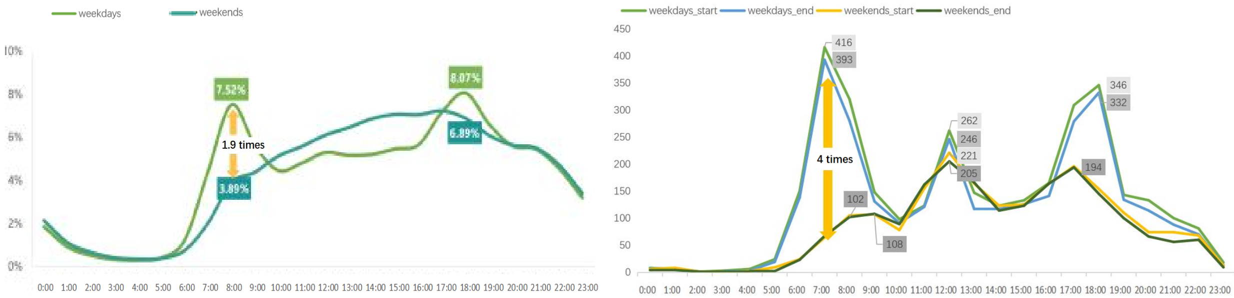

Figure 5. Timing patterns of city and campus shared bicycle use.

3.2 Spatial Patterns of Bike Usage at University

Weekday bike data was analyzed using heat maps to examine the distribution of starting and ending points. Starting points showed an even distribution in teaching buildings and residential areas, with lower densities in specific locations. In the teaching area, higher concentrations were observed near certain buildings and gates. In the residential area, clear clusters were observed in specific locations. The distribution of ending points followed a similar pattern but with changes in the locations of clustered areas. Notable clusters were found in different places within the teaching and residential areas. Overall, bike aggregation points within the campus aligned with each other on weekdays, but certain areas had a higher likelihood of bike clustering, suggesting the need for timely redistribution.
The same analysis was applied to weekend bike data. The uniformity and low-density areas remained consistent with weekdays, but significant changes occurred in the locations of clustering points. Starting points showed clustering near specific areas, while other clusters were no longer significant. In the residential area, certain locations maintained their clustering patterns, and a new clustering point emerged. The distribution of ending points also showed changes in clustering patterns. Significant clusters appeared in different areas within the teaching and residential zones. Consequently, on weekends, there was a tendency for bike redundancy in certain locations and a potential shortage of bikes in others.

Figure 6. Campus weekday and weekend bike-sharing origin and destination heat map.

3.3 Spatial-Temporal Contradictions

The most significant issue observed is the excessive bike usage during peak hours. On weekdays, peak periods occur from 7:00 to 8:00, 12:00, and 17:00 to 18:00. On weekends, peak periods are at 12:00 and 17:00. Urgent improvement is needed to address these peak phenomena.

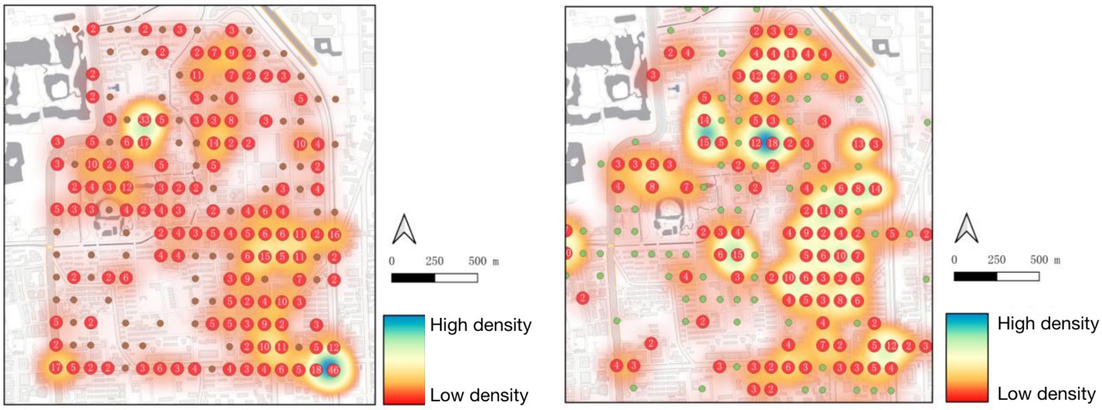

Figure 7. Campus weekdays 7:00-8:00 bike sharing start and end points.

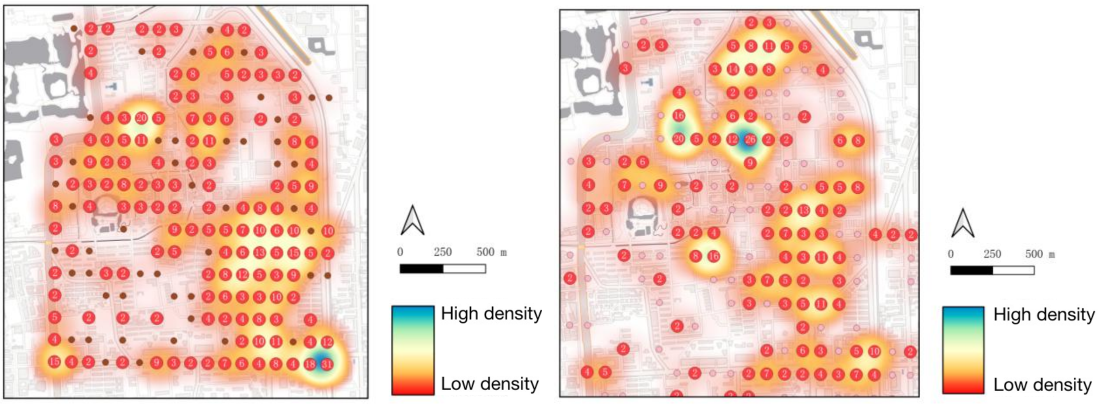

Figure 8. Campus weekdays 12:00 bike sharing start and end points.

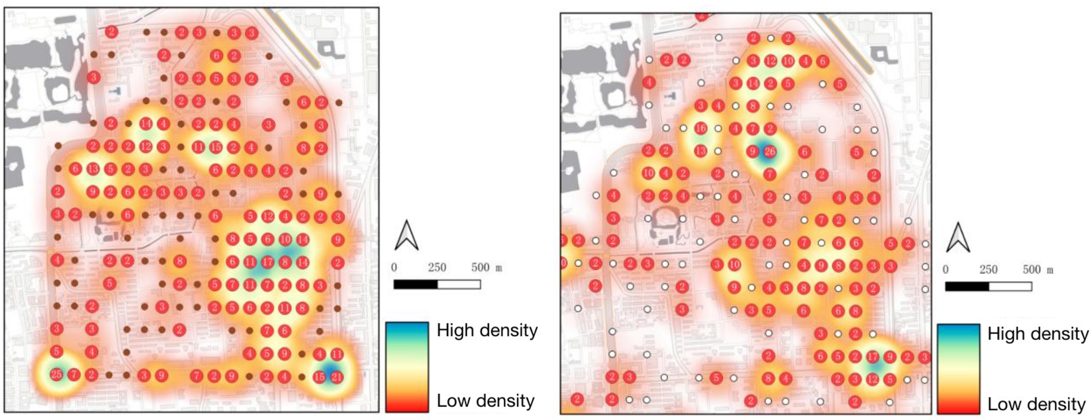

Figure 9. Campus weekdays 17:00—18:00 bike sharing start and end points.

During weekdays from 7:00 to 8:00, bike usage concentrates around Guanchou Garden and Taoli. At 12:00, Guanchou Garden remains a prominent starting point, with students traveling near the main building. Ending points are primarily Qingfen Garden, Guanchou Garden, and Zijing Cafeteria. From 17:00 to 18:00, starting points are concentrated around Guanchou Garden, Qingfen Garden, and the central axis in front of the main building. Guanchou Garden is the main ending point during this time.

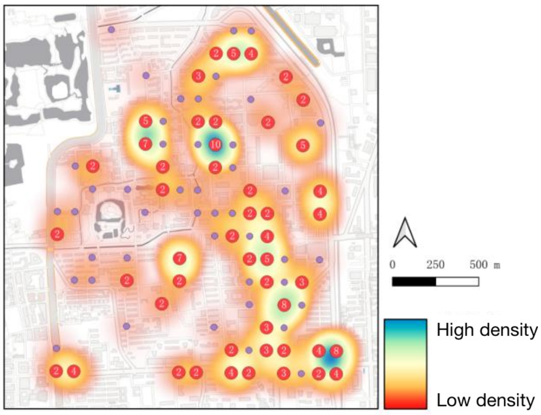

Figure 10. Campus weekends 12:00 bike sharing start and end points.

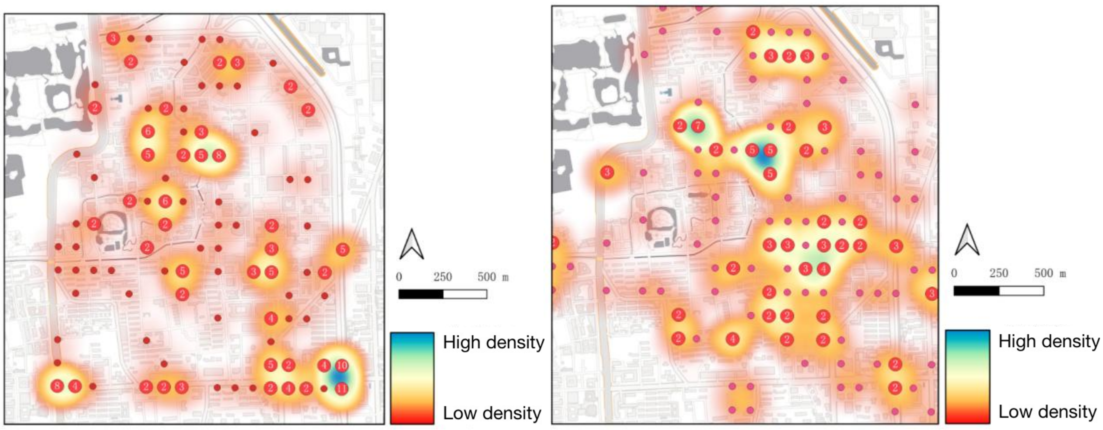

Figure 11. Campus weekends 17:00 bike sharing start and end points.

On weekends, peak hours are at 12:00 and 17:00. Starting points revolve around Qingfen Garden and Guanchou Garden, with even distribution in other areas. Ending points are primarily located in the residential area, specifically Zijing Cafeteria, Qingfen Garden, and the Library of Lee Wen Zheng. Qingfen Garden and Guanchou Garden are the main starting points during weekend peak hours, while the choice of ending points shows less regularity in terms of location.

3.4 Factors influencing the spatial and temporal distribution pattern

(1) Dependent Variable

To investigate the spatial-temporal conflicts of on-campus bike-sharing discussed earlier, the dependent variable was chosen as the number of bikes at the starting and ending points within spatial grids.

(2) Construction of Independent Variable System

In this study, a model prediction approach was adopted to assess the effects of different factors on bike-sharing usage. Therefore, commonly used Point of Interest (POI) data and road attribute data were selected, street morphology indicators were incorporated to construct the prediction model. Due to the excessive categorization of service facilities in the original POI data, which represents the density of service facilities, this study followed the research method of Wen Chuan et al. (Wen, C. et al, 2022) and classified all POIs into five categories based on the statistical quantity of POIs, sorted from smallest to largest. Regarding road attribute analysis, existing studies (Xu, B. & Lu, Q. 2023) only considered physical parameters such as intersection density, main road density, and secondary road density. In this study, we added street morphology indicators proposed by Harvey et al., such as street width, continuity, building density, and aspect ratio, to improve the accuracy of the regression model (Harvey, C., et al, 2017).

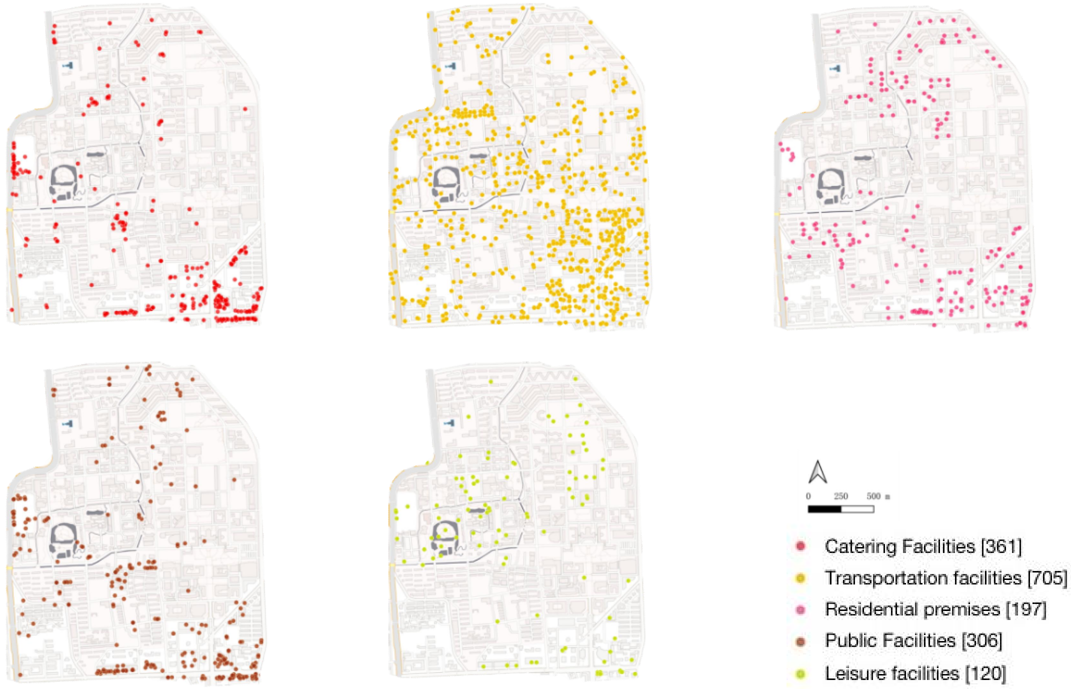

Figure 12. Campus POI.

(3) Analysis of Influencing Factors

SPSS and Python were chosen as the tools for model construction. After selecting appropriate predictor variables from potential factors, multiple linear regression (MLR) was used to predict the bike docking situation influenced by different factors (Feng et al., 2022).

- First, each potential predictor variable was subjected to univariate regression analysis with the five time period datasets. Only predictor variables that showed significance in the univariate models (P-value < 0.05) were retained.
- To avoid affecting the results of subsequent models, the variables were tested for multicollinearity using the variance inflation factor (VIF), and variables with VIF values greater than 10 were removed from the model. After removing these variables, the remaining variables had VIF values ranging from 0 to 10, indicating the absence of multicollinearity.

- For each predictor variable remaining after Step 2, the R-squared value between the individual factor and the dependent variable was calculated using Python. The predictor variables were then added to the regression model in descending order of their R-squared values within the same layer of univariate regression.
- The final MLR model was constructed using the selected predictor variables, and variable coefficients and model accuracy were calculated. Finally, seven MLR models were built since there was no apparent correlation pattern found for the bike starting points at 12:00 and 17:00-18:00 on weekdays, as well as the bike starting points at 17:00 on weekends.

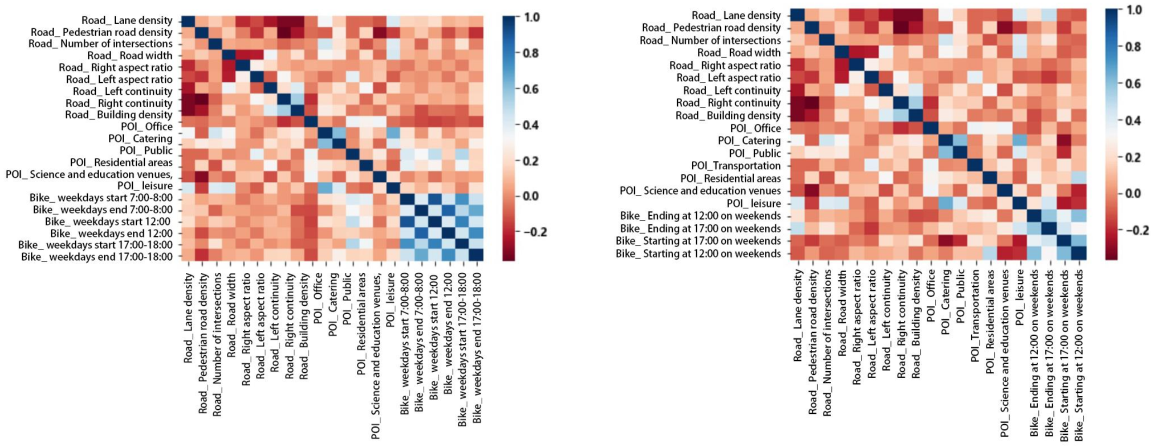

Figure 13. Correlation coefficient matrix heat map for weekday and weekend.

Bicycle density at different times			transportation facilities	road length	residence	junction	teaching building	office	R²
weekday	start	7:00—8:00	0.369	0.218	0.216				0.086
		12:00	0.501	0.143		-0.004			0.228
		17:00-18:00	0.494			0.027			0.233
	end	7:00—8:00	0.321						0.093
weenkend	start	12:00			0.511				0.229
	end	12:00		0.212					0.034
		17:00		0.696		0.57	0.037	0.07	0.904
Average			0.421	0.317	0.364	0.198	0.037	0.07	0.258

Table 3. Campus weekend and weekday bike-sharing multiple linear regression models.

During weekdays, the peak bike starting points at 7:00-8:00 were primarily influenced by the density of transportation facilities, followed by road length and residential areas. The ending points were largely influenced by entrance and exit facilities, indicating that the starting points were mostly residential areas and the ending points were various facility entrances and exits. For the peak at 12:00, the starting points were influenced by entrance facilities and positively affected by road lanes, while negatively affected by intersections. The ending points were relatively weakly influenced by the built environment. For the peak at 17:00-18:00, the starting points were strongly influenced by entrance facilities and intersection quantity. To improve transportation during peak periods and address on-campus traffic issues, road infrastructure should be more evenly distributed in terms of road length and the distribution of entrance and exit facilities should be more balanced, reducing the frequency of intersection occurrence. In terms of facility distribution, the distribution of residential areas should also be more balanced, as the separation between teaching areas and residential areas could lead to difficulties in bike usage and traffic congestion.

During weekends, the density of residential areas and road lanes influenced the bike starting points at 12:00, while road lane density, intersection quantity, educational facilities, and office facilities influenced bike parking at 17:00. Therefore, in terms of road infrastructure, the distribution density of entrance and exit facilities should be improved, and the distribution of road lanes and intersection quantities should be more balanced, avoiding excessive concentration. Additionally, the distribution of residential areas, educational areas, and office areas should be more balanced to reduce the number of bikes during peak periods and address other traffic hazards.

3.5 limitation

However, this study also has limitations. In terms of roads, further investigation should focus on bike riding routes rather than solely relying on simple OD distance statistics. Improving existing university roads could involve increasing the width of popular bike lanes, creating separate entrances convenient for bike parking, and reducing the number of intersections. Regarding facility distribution, during renovations, a functional reorganization of teaching areas, office areas, and residential areas could be considered. Public classrooms could be set up near residential areas to address the issue. Further research could employ methods such as offline questionnaires and manual surveys to assess available unused spaces in public classrooms for various functions, such as dining facilities, to avoid a disconnect between residential areas and teaching areas.

4. Conclusion

Shared bikes has become an essential means of transportation for many universities. However, existing literature mostly relies on subjective judgments or predictive models to understand its patterns, lacking objective recommendations for improving its relationship with the built environment. This study analyzed the spatiotemporal patterns of bike riding and parking on weekdays and weekends at Tsinghua University. To address the main contradictions related to the spatiotemporal issues of bike sharing and understand the causes of peak periods, MLR models were established using Python and SPSS.

Our model exhibits a high R-squared value, indicating the inadequacy of shared bikes for daily use and the pressure they exert on the built environment. The number of entrances, total road length, and intersections consistently have the greatest impact on shared bike usage. This highlights the severity of clustered bike parking at entrances, roadsides, and intersections, leading to conflicts and accidents in vehicle lanes and entry/exit spaces. Designing parking spots can help alleviate these conflicts. Residential density also significantly affects shared bike usage, while integrating teaching and office spaces can adjust bike distribution to some extent. Thus, shared bike quantity regulation should primarily focus on residential areas, ensuring prompt replenishment during peak usage and transporting excess bikes for repair in dormitory areas.

The contribution of this study is that, firstly, the research method applies a large-scale shared bike spatiotemporal pattern judgment model to a smaller scale study and validates its effectiveness.

Secondly, existing studies often focus on building more efficient shared bike prediction models, whereas this study emphasizes exploring improvement strategies for the built environment affected by shared bikes and provides references for planning and design. Lastly, the research findings indicate the limited carrying capacity of the built environment for shared bikes. To enhance the efficiency of shared bike usage, we should focus not only on increasing their quantity but also on considering the built environment adaption.

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