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Analysis of the Use Characteristics and Influencing Factors of Shared Bikes

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Abstract. As mobile communications technology and the Internet advance rapidly, stake less shared bicycles have rapidly gained popularity worldwide, becoming an essential approach to alleviating urban traffic congestion and enhancing the efficiency of public transportation links However, with the widespread use of shared bikes, problems such as irrational scheduling, imbalance between supply and demand, and difficulties in parking management have been exposed. To solve these problems, this study analyzes the usage characteristics and influencing factors based on big data of shared bikes in New York City. This study employs data visualization, ordinary least squares regression (OLS) model and geographically weighted regression (GWR) model to provide an in-depth analysis of the usage patterns of shared bicycles. The results show that the use of shared bicycles has significant spatial and temporal characteristics, which are mainly influenced by factors such as population density, transportation infrastructure and surrounding dining facilities. Commuting demand is evident Especially during weekday morning and evening rush hours, between commercial districts and residential neighborhoods; while in areas with dense food and beverage facilities, the frequency of use increases significantly during lunch and dinner hours.

Keywords: shared bikes, big data, New York.

1. Introduction

The research topic of this paper is the study of the characteristics of the use and some movements of shared bikes. With the increase of urban population and traffic density, traditional ground transportation and public transport systems have become congested and inefficient, making bicycles a more attractive option for commuters due to their convenience, speed, and environmental benefits

It can be said that, as an eco-friendly public transport resource with a large scale and low use and maintenance costs in the current public transport system, shared bikes have been deeply involved in the daily life of many urban residents.

On this basis, to meet the large-scale demand for shared bikes, the diversity of demand distribution, coupled with the technical conditions provided by the development of mobile communication tools and Internet technology, the process of piling-free shared bikes began. Although no pile after Shared cycling has larger increase in flexibility, it is also because the diversity of commuters' destination and different destination area of Shared cycling in different periods of different demand to a certain extent reduces the Shared cycling scheduling and response speed, the rationality of the distribution space, with the fluency of docking user demand.

Therefore, through the study of the distribution data of shared bikes, With the development of big data technology, it is possible to deeply mine and analyze the data of shared bicycles, and through the analysis of user behavior patterns and demand fluctuations, it is possible to further optimize the scheduling strategy and improve the utilization rate and service quality of bicycles. It will be necessary to rationalize and improve the configuration density of different regions and different regions for the need to improve the speed, accuracy and flexibility of the scheduling of shared bikes. This paper bases the focus of research on the description of the use characteristics of the shared bikes and the characteristics of the mobile track and based on the influence of the distribution of the types of facilities in the surrounding areas and the area, to provide reference when selecting the destination for the scale scheduling of shared bikes in the future.

As an emerging mode of urban transportation, shared bikes have an important influence on the theoretical research of urban micro traffic flow. Literature [1] and [2] have analyzed the relationship between the pattern used of shared bikes and the urban environment, which provides a new perspective on this field. At the same time, this study draws on the methods of literature [3] and [4], improves the methods of shared bike demand prediction and scheduling research, expands the application of big data analysis in this field, and provides a new analytical tool and method framework for subsequent research.

In the practical application level, the findings of this study will aid in guided the practice of urban traffic management departments and bike-sharing enterprises. For example, the study on the optimization of shared bikes and rail transit in [5] and [6] can provide decision support for the optimization of connection services in urban public transport system. In addition, this study has promoted the medium-and long-term development of the bike-sharing industry, among which the study of the intelligent dispatching platform in the literature [7] has significantly improved operational efficiency and promoted the sustainable development of bike-sharing services. At the same time, as shown in literature [8] and [2], an in-depth analysis of the use of shared bikes and their impact on the environment helps the public and policy makers to realize the role of shared bikes in the sustainable urban transportation system and promote the popularity of green travel.

2. Methods

In the first part: First, understand the research direction of shared bikes through consulting the literature, and determine the clear direction of topic selection. According to the area and type of data acquisition, determine the direction of research, understand the research status of relevant directions and relevant research methods, and identify the research theory. On this basis, the research content and technical route are put forward.

The second part: The main research content is the data preprocessing part, including the acquisition of shared bike travel data, research area vector data, raw data preprocessing, null processing, eliminating outlier values, etc., to meet the requirements of subsequent experiments and improve the accuracy of data analysis.

Part three: Visual analysis of the shared bike data, Visualization of the data separately: Visual analysis of the number of bike-sharing rides per hour, Visual Analysis of Bike Sharing Usage Duration, Visual Analysis of Bike Sharing Ride Distance, Analysis of the Proportion of Bike Sharing Usage on Working Days and Non-Working Days, Comparative Analysis of Morning and Evening Peak Hotspot Maps.

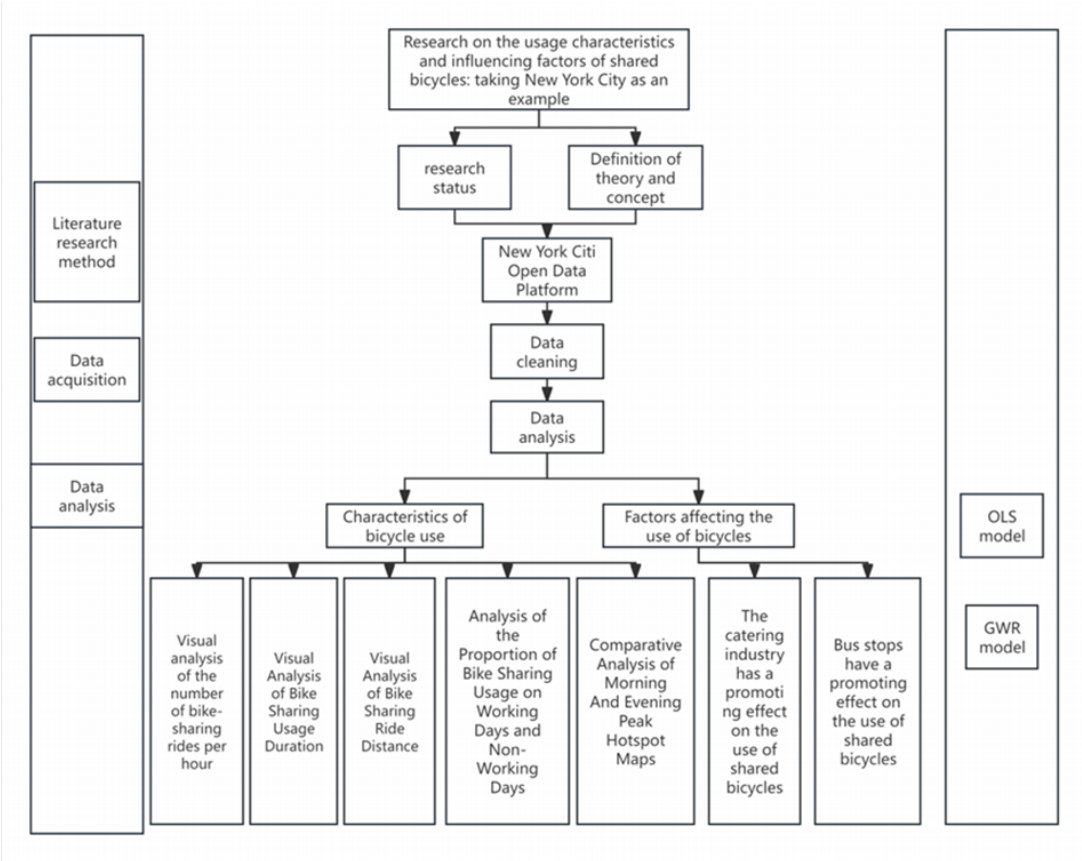

Figure 1. Technical Road map.

2.1. Literature research method

This study conducts extensive and systematic access of relevant literature in the field of bike-sharing at home and abroad, not limited to journal articles, academic works, but also policy reports, industry analysis, and gray literature, to fully understand and grasp the latest progress and dynamics of bike-sharing research. Through meticulous review and comprehensive analysis of prior research findings, a range of factors that exert a notable influence on the utilization of shared bicycles have been identified and summarized. These factors encompass multiple facets, including socio-economic conditions, urban planning, transportation infrastructure, and individual habits. This establishes a firm theoretical groundwork and offers substantial data support for the subsequent stages of model development and empirical examination.

2.2. Least squares regression (OLS) model analysis

In this study, the OLS (Ordinary Least Squares) model, a well-established linear regression analysis technique, is employed to investigate the quantitative relationship between the identified influencing factors and the utilization of shared bicycles. The model setting follows the form of $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n$, where y represents the use of shared bikes, x_1 to x_n represents different influencing factors, such as traffic facility density and population density, and β_0 to β_n is the corresponding regression coefficient, reflecting the influence of each factor on the use of shared bikes. By minimizing the residual sum of squares, which is the sum of the squared differences between the observed values and the predictions made by the model, the optimal regression coefficients are determined. This process yields a linear model that most accurately captures the underlying patterns and regularities in the data. Moreover, this study used the F test to assess the overall significance of the model, the T-test to test the significance of individual regression coefficients, and R square to measure the good fitness of the model, ensuring the accuracy and reliability of the analysis results. Through the analysis of the OLS model, the factors that have a significant influence on the use of shared bikes can be screened out to provide directions for further in-depth research.

2.3. GWR analysis

For the unique heterogeneity of spatial data, this study introduced a geographically weighted regression model (GWR) for in-depth analysis. The GWR model takes into full account the non-stationarity of the variable relation at the spatial location by establishing independent local regression equations for the observation points at each geographical location. This means that, unlike the global uniform regression coefficient of the OLS model, the regression coefficient of the GWR model varies with geographical location and can more finely capture spatially local features and differences. The core of the model lies in the construction of the spatial weight matrix, which assigns weights according to the spatial distance between the observation points. The choice of the weight function (such as Gaussian function, double square exponential function, etc.) directly affects the accuracy of the model's characterization of the spatial relationship. The parameters were estimated through the application of the maximum likelihood estimation method, which involves iteratively refining the likelihood function to arrive at estimates for each local regression coefficient. The implementation of the Geographically Weighted Regression (GWR) model not only uncovers the spatial distribution patterns of the factors influencing shared bike usage but also furnishes a scientific rationale for devising differentiated management and planning strategies for shared bike systems.

2.4. Data source

This study selects the research object for New York city Shared cycling use characteristics and influencing factors, the required data to share the use of bicycle data, through the New York Citigroup sharing cycling data open platform, selected the New York city in February 2024 Shared cycling use data, data type for csv data, because the data is too large, we selected more than 2001 million data analysis. The fields of the data include ride_id, rideable_type, started_at, ended_at, start_station_name, start_station_id, end_station_name, end_station_id, start _ lat, start _ lng, end _ lot, end _ lng, member_casual. The New York City OSM dataset was downloaded from the data open platform, with the dataset containing buildings, landuse, nature, places, points, railways, roads, waterways.

3. Results

3.1. Visual analysis of the number of bike-sharing rides per hour

By using R language for New York Shared cycling per hour for visualization, to explore the Shared bike in the period of the day distribution using characteristics, first need to use the starting time of Shared bike grouped per hour, then to the sharing of the starting point of the data in New York city block group data in the number of statistics, create a new entry, through the entry making line chart get figure 2.

As can be seen from Figure 2, shared bikes have obvious tidal properties. The use period of shared bikes starts at 5 am, and the number of bike users is gradually increasing. During this period, there is a morning peak and an evening peak. Compared with the morning peak, the evening peak is higher than the morning peak, and it is the highest number of cycling period in the day. The reason for this kind of phenomenon has the wrong peak go to work system, a few units to alleviate traffic pressure, adopted wrong peak go to work system. This means that some employees may not start work until the morning rush hour, thus reducing the use of shared bikes during the morning rush hour. Consequently, these employees depart from work during the evening rush hour, thereby elevating the usage of shared bikes during this period. Furthermore, as the pace of life accelerates and nightlife becomes more diverse, an increasing number of individuals opt to engage in social, recreational, and shopping activities during the evening. These nighttime activities increase the use of shared bikes during the evening rush hour, making the amount higher than the morning peak. The main purpose is commuting, when residents

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travel from the residential area to the work area or study area. During the evening rush hour, in addition to commuting cycling, residents are also returning from work or study areas, as well as other nighttime activities. This diversity of cycling purposes makes the evening peak cycling larger; travel habits change, with the popularity and convenience of shared bikes, more and more residents develop cycling habits. During the evening rush hour, in addition to the necessary commuting rides, many people also choose to ride shared bikes for short trips or physical exercise, further increasing the amount of evening rush hour rides.

The morning rush hour of bike-sharing is from 7 am to 10 am, and the peak is at 8 am. The reason for this phenomenon is the commuting needs. On weekdays, most residents need to arrive at their workplaces on time, so there will be concentrated travel demand in the morning. During this period, as a convenient and flexible way of travelling, bike sharing has become the first choice for many residents to commute. On the other hand, traffic is heavy in the morning, where urban traffic is often congested by the influx of commuter cars. Due to their small and flexible characteristics, shared bikes have higher traffic efficiency on congested roads, thus attracting many residents seeking to reach their destinations quickly.

The evening rush hour for bike-sharing is from 3 PM to 6 PM, and the peak is at 5 PM. The first reason is like the morning rush hour. Many enterprises and institutions work time is concentrated between this period, which leads to many employees who choose shared bikes as commuting tools to return to their residence during this period, thus forming the evening rush hour. Some schools leave school early, and parents may need to use shared bikes to pick up their children. This process not only boosts the utilization of shared bikes but may also bring forward the commencement of the evening rush hour. On the other hand, residents start to prepare for social entertainment or shopping activities at night during this time and choose shared bikes as a means of transportation to their destinations, resulting in the evening rush hour.

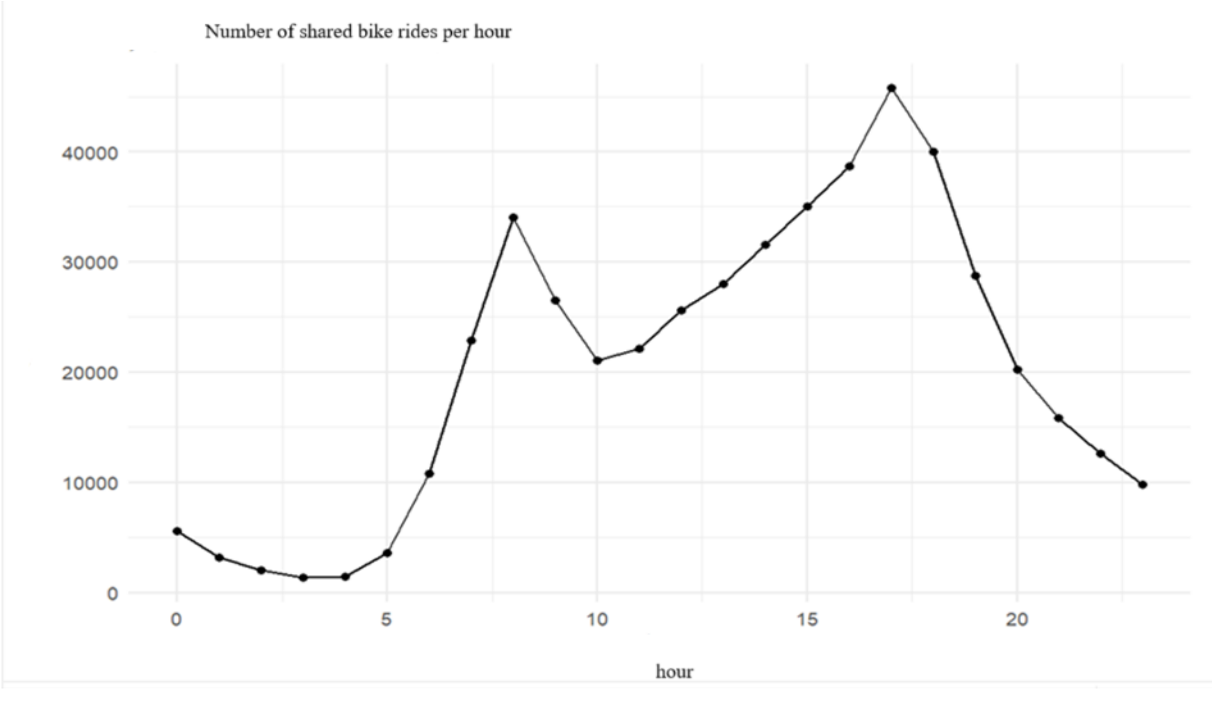

Figure 2. for Visual analysis of the number of bike-sharing rides per hour(Data source: R language).

3.2. Visual Analysis of Bike Sharing Usage Duration

Through R language of Shared cycling duration visualization, to explore the characteristics of Shared cycling duration, by sharing the start time and the end time of Shared cycling use duration, produce a

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new statistical entry, the duration of 5 minutes for group grouping, using r language into a histogram, get figure 3.

As can be seen from Figure 3, the cycling duration of shared bikes is mostly within 5 minutes to 30 minutes, among which the number of users using them in 5 minutes to 10 minutes is the most frequent, followed by 10 minutes to 15 minutes. A ride time of 5-10 minutes corresponds to shorter trips, indicating that shared bikes mainly meet users' needs for short trips. In cities, many people choose shared bikes as a means of transportation between public transport stations (such as subway and bus stations) and their destination, or for short-distance shopping and leisure activities. The duration of shared bikes is 5-10 minutes, which not only reflects the large demand for short-distance travel, urban traffic congestion and the convenience of using shared bikes, but also reflects the information of urban planning, traffic facilities layout and users' behavior habits.

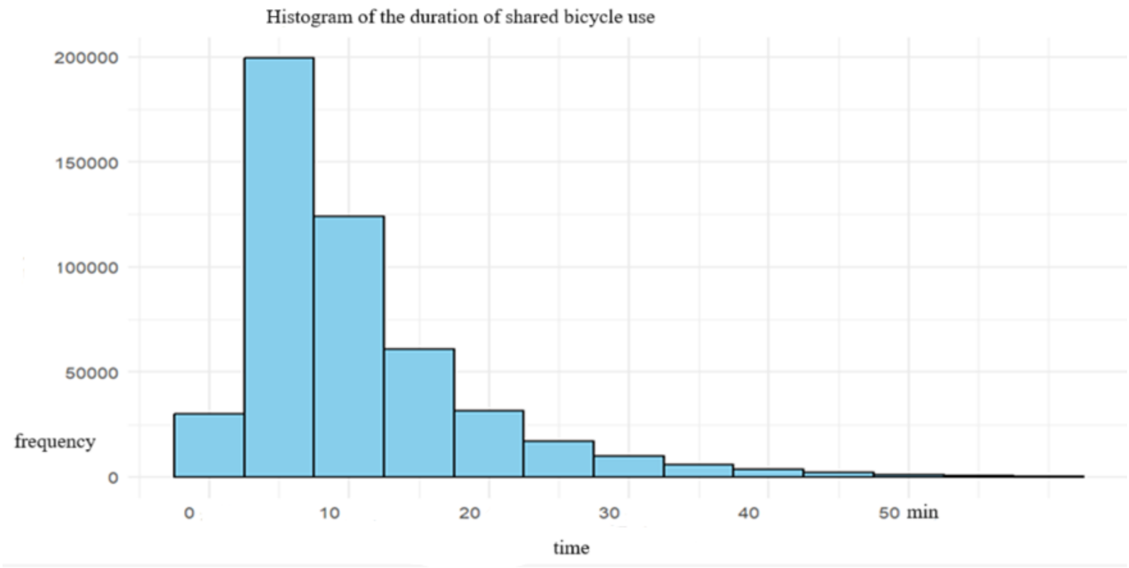

Figure 3. where the Visual Analysis of Bike Sharing Usage Duration(Data source: R language)

3.3. Visual Analysis of Bike Sharing Ride Distance

The cycling distance of the shared bike is visualized in R language to explore the distance characteristics of the shared bikes. By calculating the linear distance from the longitude and latitude of the starting point and the shared bike data, grouping the cycling distance by 1000m, and drawing the histogram is drawn.

Can be seen from figure 4 Shared cycling distance most within 0 to 3000 meters, 0 to 1000 meters and 1000 meters to 2000 meters of the largest users, the latter slightly higher than the former, most users concentrated in this interval, followed by 2000 meters to 3000 meters, more than 3000 meters after the bicycle use user number. The largest number of users is 0 to 1000 meters and 1000 to 2000 meters, which could mean that many users choose shared bikes as a bridge between the public transport station (and the destination. This approach not only improves travel efficiency, but also reduces the time and physical exertion of walking, which reflects the needs of urban residents for short trips.

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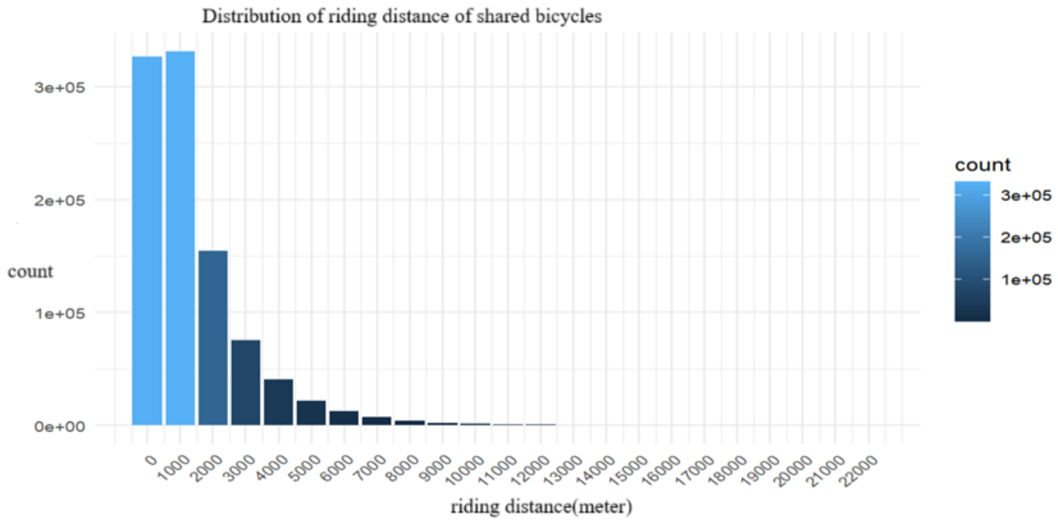

Figure 4. in Visual Analysis of Bike Sharing Ride Distance(Data source: R language)

3.4. Analysis of the Proportion of Bike Sharing Usage on Working Days and Non-Working Days

Observations reveal that the order data volume on weekdays is higher than that on non-weekdays. This may be attributed to the more significant traffic congestion on weekdays, leading to more commuters potentially choosing bike sharing combined with public rail transit for their trips. Therefore, there are more and more fixed mandatory travel demands on weekdays. Conversely, travel demands on non-weekdays are relatively less fixed, resulting in a decrease in the demand for bike sharing.

A statistical analysis of the average usage frequency on weekdays and non-weekdays shows that the average usage frequency on weekdays is 148,043 times, while the average usage frequency on non-weekdays is 119,218 times. The demand for bike sharing is greater on weekdays.

This suggests that the primary role of bike sharing is to fulfill the short-distance travel requirements of residents.

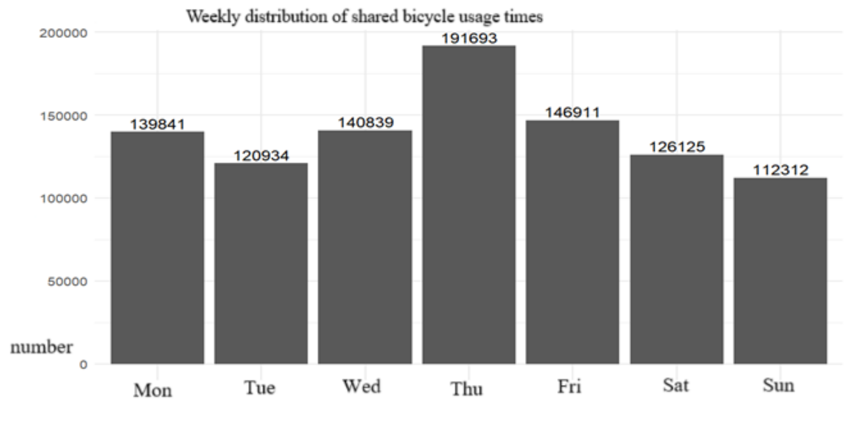

Figure 5. in Visual Analysis of Bike Sharing times(Data source: R language)

3.5. Comparative Analysis of Morning and Evening Peak Hotspot Maps

Comparative analysis showed that early morning and evening hotspots were relatively similar, all concentrated in southern Manhattan, western Queens, and northwestern Brooklyn. Cold spots are mainly

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distributed in the northern part of the Bronx and the eastern part of Queens. There is a broader range of bicycles that use hotspots during the evening peak compared to the morning rush hour. The reason for this is the similarity of hotspots in the morning and evening, possibly reflecting the greater tendency to commute using shared bikes during both periods. Southern Manhattan, western Queens, and northwest Brooklyn serve as the main commercial and residential areas in New York City, attracting many bike-sharing users. During the morning rush hour, individuals primarily commute from their homes to work, resulting in relatively concentrated hotspots. In contrast, during the evening rush hour, people not only return home from work but also engage in various activities such as shopping and entertainment, leading to a broader distribution of hotspots. The northern part of the Bronx and eastern Queens are relatively remote, inconvenient, and may lack adequate bike-sharing facilities or a suitable cycling environment. Southern Manhattan, western Queens and northwestern Brooklyn have a better transportation network and more commercial facilities, attracting more bike-sharing users. Hotspots are usually areas with high economic activity and high population density. As the financial center of New York, southern Manhattan attracts many office workers and tourists, the use of shared bikes is high. During the evening rush hour, the utilization of shared bikes broadens as individuals engage in more post-work activities, including shopping, dining, and entertainment.

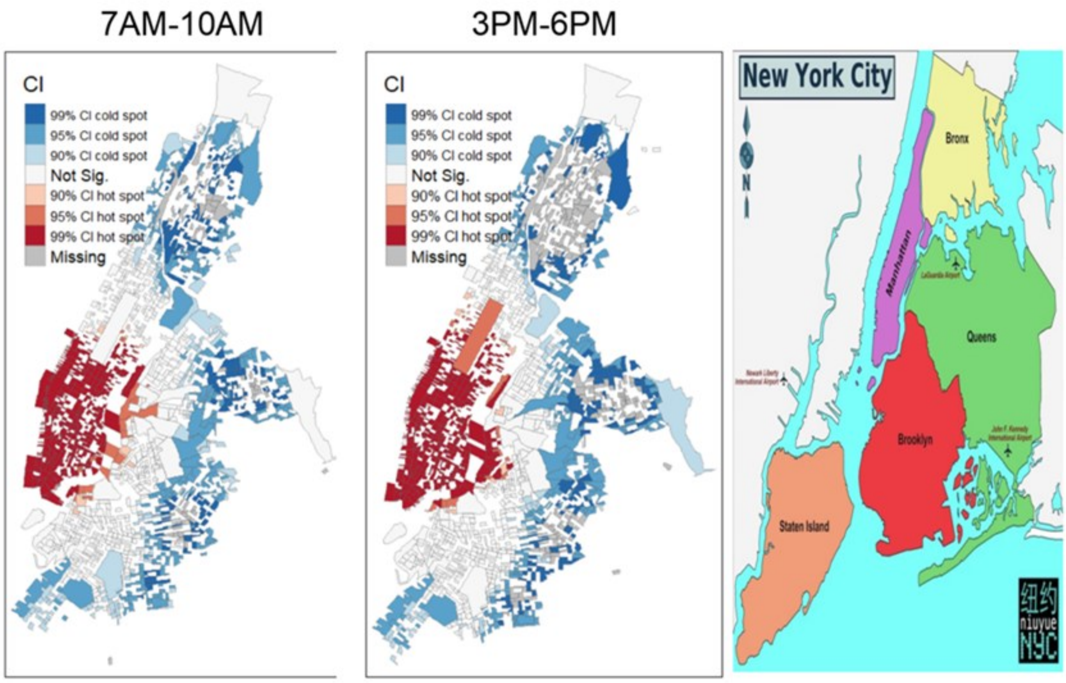

Figure 6. Thermal density at the morning and evening peaks(Data source: R language)

3.6. Model construction and analysis

3.6.1. OLS regression model construction

The OLS (Ordinary Least Squares) regression model is a widely utilized linear regression model in statistics for estimating the parameters that describe the linear relationship between the independent variable (predictor) and the dependent variable (response). The basic formula for the OLS regression model is as follows:

$$y_i=\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\cdots+\beta_p x_{ip}+\epsilon_i$$

The y_i i is the dependent variable (response variable).

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Xi 1, xi2..., xip is the independent variable (predictor variable) of the observed value.

β 0 is the intercept term.

β 1, β 2,...., β p is the regression coefficient of the independent variable, indicating the degree of influence of the respective variable on the dependent variable.

ϵ I is the error term of the observed value and represents the part that the model fails to explain.

3.6.2. Selection of the variables

This paper studies the influencing factors of the use of shared bikes, so the dependent variable is the number of uses of shared bikes (ttip), the independent variable is the number of restaurants (ttfood), the number of population (pu), the number of schools (ttschool), and the number of buses (ttbus).

3.6.3. Analysis of the OLS data

According to the graph, ttfood, popu, ttbus passed the significance test. It can be concluded that catering facilities, transportation facilities and the number of people have a great impact on the use of shared bikes. Catering facilities: weekday dinner time, many users will choose to ride Shared cycling to restaurants or take-away meals, so catering facilities intensive area Shared cycling use times will increase significantly: catering facilities as an important part of life service, its distribution directly affects the users travel demand and travel mode and promote the use of Shared cycling. Transportation facilities: Transportation facilities such as bus stops and subway stations are important connections for the use of shared bikes. Users often use Shared cycling from home to bus station or subway station "the last kilometer" travel, or from the bus station, subway station to the destination connection: the use of the subway outbound traffic facilities directly affect the use of Shared cycling, because many people distribution will drive the use of Shared cycling. Population number: Population number is the basic factor that determines the number of shared bikes used. In areas with high population density, the travel demand is more concentrated, and the demand for shared bikes is also higher. More potential users mean greater market demand, which drives the increased use of shared bikes.

```
Call:
lm(formula = ttrp ~ ttfood + popu + ttschool + ttbus + 0, data =
cor_matrix_data_new)

Residuals:
    Min      1Q  Median      3Q     Max
-4.2887 -0.3999 -0.1495  0.2214  8.7364

Coefficients:
         Estimate Std. Error t value Pr(>|t|)
ttfood    0.31290    0.03729   8.392  3.6e-16 ***
popu      0.07235    0.03508   2.063   0.0396 *
ttschool  0.01631    0.03456   0.472   0.6371
ttbus     0.34115    0.03677   9.277  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8334 on 586 degrees of freedom
Multiple R-squared:  0.3089,    Adjusted R-squared:  0.3042
F-statistic: 65.48 on 4 and 586 DF,  p-value: < 2.2e-16


        Shapiro-Wilk normality test

data:  residuals(model_2)
W = 0.77618, p-value < 2.2e-16
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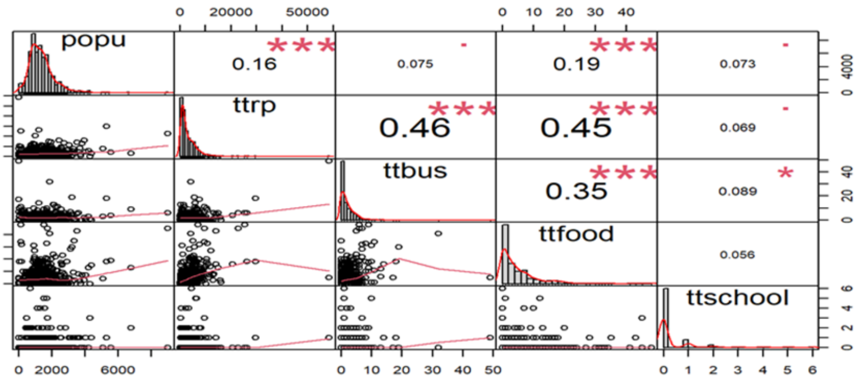

Figure 7. for OLS analysis(Data source: R language)

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3.6.4. Geographically Weighted Regression Analysis

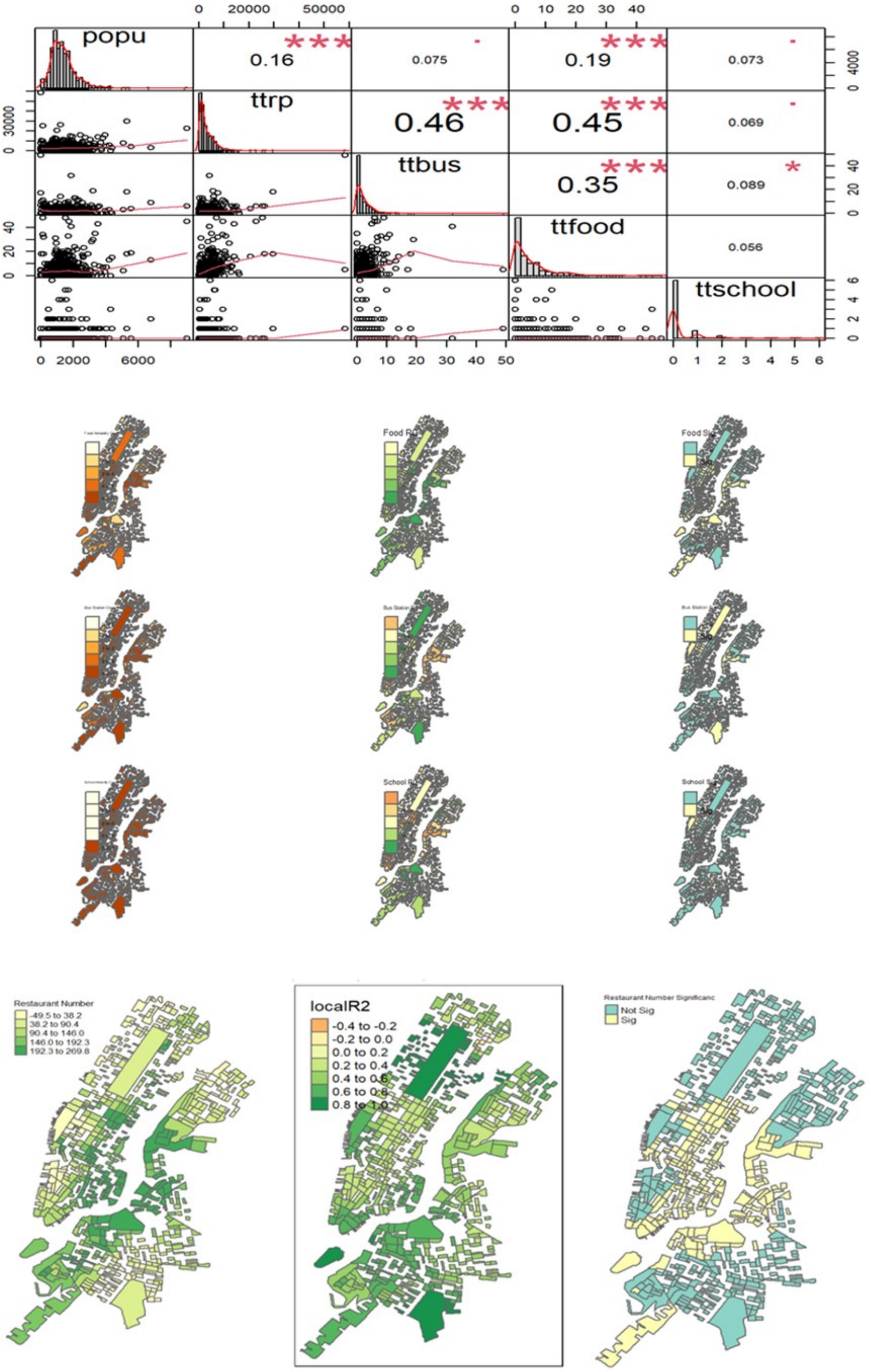

Figure 8. Geographically Weighted Regression Analysis(Data source: R language)

As can be seen from the figure catering facilities are mainly distributed in southwest Manhattan, northern Brooklyn and western queens, compared with the GWR significant distribution can be seen that the distribution of catering facilities and the distribution of the significance, in catering facilities dense area, due to the combined action of population flow and business vitality, catering facilities number of Shared

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cycling usage may be more significant. This explains why the GWR is more significant in these regions. In areas with dense dining facilities, People are more inclined to utilize shared bikes for dining purposes. because they provide a convenient and flexible way to travel.

Your revised sentence is correct and clearly conveys the intended meaning. It states that individuals are more likely to choose shared bikes as a mode of transportation for dining activities.

The number of bus stops is concentrated in Manhattan, Brooklyn, Queens, the Bronx and Staten Island, with shared bikes used more frequently, possibly because they have become an ideal vehicle for short distances during transfers. Especially in the morning and evening rush hours, shared bikes can quickly evacuate the people of bus stops and relieve traffic pressure. High transfer demand, matching of use scenarios, convenient parking of shared bikes, improved environmental travel awareness and data support, etc. Together, these factors contribute to the high frequency of use of shared bikes near bus stops.

Schools have no significant impact on the use of shared bikes, because the distribution of schools does not match the distribution of shared bikes. Schools in New York City may be scattered in different parts of the city, while the bike-sharing strategy may focus more on crowded areas such as commercial districts and transportation hubs rather than around all schools. This makes it difficult for some students to use shared bikes conveniently. The transportation facilities around the school are perfect. Some schools may already have perfect public transport facilities, such as subways and buses, which reduce students' demand for shared bikes. School safety management requirements. Some schools may have certain restrictions on students travel modes for safety reasons. For example, students under a certain age are not allowed to ride bicycles to and from school, or special requirements for the use of shared bikes.

4. Conclusion

With the swift advancement of mobile communication tools and Internet technology, dockless bike sharing has gained rapid popularity globally and emerged as a significant method to alleviate urban traffic congestion and enhance the efficiency of public transportation connections. This paper focuses on New York City as the subject of study and examines its shared bicycle usage data. The objective is to investigate the characteristics and influencing factors of shared bicycle utilization, thereby offering insights for optimizing the allocation of urban transportation resources.

Based on the data on shared bicycles in New York City, this paper provides an in-depth analysis of the characteristics of shared bicycles and their influencing factors. Through time series analysis, spatial distribution model and regression model, the important role of shared bicycles in daily travel and their use in different time and space backgrounds are revealed. The results show that shared bicycles are mainly used to meet the needs of residents for short distance travel and show significant differences between working days and non-working days, as well as morning and evening peak characteristics. At the same time, by constructing OLS (ordinary least squares) and GWR (geographically weighted regression) models, the influence of various factors including population, catering facilities, and bus stops on the use of shared bicycles is discussed, which provides a scientific basis for the deployment and scheduling of shared bicycles in urban planning. The following conclusions were reached:

(1) Cycling behavior characteristics, spatio-temporal characteristics and spatio-temporal patterns

Time characteristics: There is a notable increase in the use of shared bicycles during weekday morning and evening peak hours, while usage decreases on weekends and holidays. Furthermore, seasonal variations are prominent, with higher utilization rates in summer compared to winter.

Spatial characteristics: Cycling hotspots are mainly concentrated in commercial areas, office areas and residential areas, while cold spots are mostly located in remote areas or areas with inconvenient transportation. At the same time, the cycling trajectory shows obvious commuting characteristics, which are highly overlapping with public transportation stations and subway lines.

Riding characteristics: Most of the riding time is less than 10 minutes, and the riding distance is short, indicating that shared bicycles are mainly used for short-distance travel. In addition, user behavior also shows a certain regularity and periodicity.

(2) Influencing factor analysis: The results of OLS regression model show that factors such as population, catering facilities, and bus stops have a significant impact on the use of shared bicycles. Among them, the increase of catering facilities and population density will promote the use of shared bicycles, while the increase of bus stops may inhibit the use of shared bicycles due to the substitution effect, thereby reducing the use of shared bicycles. The regression was carried out according to the GWR geographically weighted regression model, which further revealed the difference in the influence of each factor in different geographical locations. In the case of food and beverage facilities, for example, the impact is more pronounced in the central urban area and relatively weaker in the suburbs. The use of shared bicycles is higher in areas with strong policy support and good publicity; Government subsidies, tax incentives and other policy measures have had a positive impact on both bike-sharing operators and users.

(3) Moderately increase the density of urban branch road networks: The GWR model shows that the density of secondary roads and neighborhood roads in urban areas is the most important factor affecting the use of shared bicycles. Combined with the current construction orientation of the city's "small blocks and dense road network", in the urban built-up area, the closed block should be appropriately opened, and the internal road should be transformed into an urban public road.

The results of this paper reveal the multi-dimensional characteristics of the use characteristics of shared bicycles and the complex influencing factors behind them. However, due to the limitations of data acquisition and research methods, there are still some shortcomings in this paper. For example, some variable data may be missing or incorrect; The study area is limited to New York City and may not be fully representative of bikeshare usage in other cities around the world.

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