COMPARING THE SPATIOTEMPORAL TRAVEL PATTERNS AND INFLUENCING FACTORS OF BIKE SHARING AND E-BIKE SHARING SYSTEMS

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ABSTRACT:

The emergence of micromobility, exemplified by bike sharing and e-bike sharing systems, has ushered in a low-carbon, environmentally friendly, and sustainable revolution in urban transportation. This transformative shift addresses the "first and last mile" challenge and holds immense potential for urban mobility enhancement. Nevertheless, the existing literature predominantly investigates the spatiotemporal travel patterns and influencing factors of bike sharing and e-bike sharing systems in isolation, overlooking comparative analyses grounded in quantitative methodologies. In order to fill this gap, this study first compares and analysis their spatiotemporal travel patterns, which are measured by travel distance, travel time, and travel volume. A Multiscale Geoweighted Regression (MGWR) model was constructed using various data sources, such as Point of Interest (POI) data, metro station data, and bus stop data, to conduct a spatiotemporal correlation analysis of land use and public transport factors with the travel volume of the shared system. Our study centers on Manhattan, New York City, utilizing data from May 2022 for both bike sharing and e-bike sharing systems. The study analysis reveals that hourly trip volumes are higher for bike sharing than for e-bike sharing, exhibiting substantial spatial variation across different regions within the city. The MGWR model's findings suggest that educational facilities exert a negative influence on bike sharing in the northeast and on e-bike sharing trips in the central region, with this impact being more pronounced on weekends. Similarly, cultural facilities negatively affect the Central region's bike sharing system and the citywide e-bike sharing system, with a milder effect during weekends. Moreover, bus stops exhibit a significant negative impact on bike sharing and e-bike sharing at Chelsea Waterside Park (only weekdays), while displaying a positive influence on both systems during weekends. To validate the MGWR model's efficacy, we conducted a comparative analysis with a Geographically Weighted Regression (GWR) model. The results demonstrate that MGWR can be more effective in correlating and quantitatively explaining the effects of different factors on spatiotemporal travel patterns. In conclusion, this study furnishes valuable insights for optimizing urban infrastructure rebalancing strategies and advancing sustainable urban infrastructure development.

1. INTRODUCTION

In recent years, shared mobility services, especially bike sharing, have experienced significant growth, offering convenient and sustainable transportation options with low carbon footprints and ecological benefits. These services address the "first and last mile" challenge in densely populated urban areas by seamlessly integrating into public transit networks like buses and subways (Molinillo et al., 2020; Böcker et al., 2020). Additionally, they have demonstrated their effectiveness in reducing traffic congestion and greenhouse gas emissions, thereby alleviating the burden on urban transportation systems. As of October 2019, bike sharing systems were either operational or in planning stages in over 50 countries worldwide. The establishment of bike sharing systems has spurred extensive research into the factors influencing their utilization. Nair et al. (2013) conducted a study on bike sharing and revealed that weekday usage rates significantly exceed weekend usage, with peak demand during morning and afternoon commuting hours, indicating the predominant use of bike sharing for weekday commutes (O'brien et al., 2014; Rixey, 2013; Zhang and Mi, 2018). Kaltenbrunner et al. (2010) and Jensen et al. (2010) illustrated substantial variations in bike sharing usage between weekdays and weekends, with usage patterns varying based on proximity to retail, educational, and workplace zones. Davis et al. (2012) investigated the travel preferences of the younger generation and found a preference for shared transportation options over private cars. Li et al. (2022) utilized a Multiscale Geoweighted Regression (MGWR) model to investigate the connection between the urban built environment and bike sharing usage in proximity to subway stations. Their findings highlight that the proximity to central business districts (CBD), hotels, and residential Points of Interest (POI) exerted the most significant influence on bike sharing use, with population density particularly impactful during weekends. Chen and Ye (2021) explored the nonlinear effects of the built environment on mobiles in Chengdu, China, revealing that both population density and employment density are key factors affecting bike sharing. Shen et al. (2018) studied bike sharing in Singapore and identified favorable factors such as diverse land uses, accessible public transportation, well-developed bike infrastructure, and promotional free rides. Lin et al. (2020) investigated bike sharing in Beijing and discovered that transportation infrastructure, including metro stations, bus stops, and the length of bike lanes, significantly affected bike sharing utilization. Parks were also found to have a more pronounced impact on promoting bike sharing during weekends and holidays than on weekdays. These studies collectively underscore the critical role of the built environment, land use diversity, and transportation infrastructure in shaping the usage patterns of bike sharing.

Building on the success of traditional bike sharing systems, many countries have introduced e-bike sharing systems, which incorporate electric bikes into their offerings. For instance, in

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2011, Germany introduced the Call A Bike system in Stuttgart, providing both conventional and e-bikes at 44 stations. This system boasts 60 e-bikes and 450 traditional bikes (Olson et al., 2015). New York's CitiBike, in 2019, announced plans to expand its fleet by adding 4,000 e-bikes. Although e-bike sharing systems are still in their early stages, they exhibit significant potential for long-distance journeys and hilly terrain. Some researchers argue that e-bike sharing holds greater promise for the future compared to traditional bike sharing (Dill and Rose, 2012; Zhou et al., 2023). This optimism stems from the electric motors integrated into e-bikes, enabling them to cover greater distances while providing increased convenience and comfort. Consequently, numerous scholars are actively investigating e-bike sharing. Ioakimidis et al. (2016) conducted a study at the University of Mons (UMONS) in Belgium to explore the characteristics and attitudes of students regarding e-bike rentals through a sharing network. The study identified specific characteristics that influence the shared use of e-bikes. In a survey conducted by Mcneil et al. (2017) , it was found that 80% of e-bike sharing users utilize e-bikes for various activities, such as shopping, socializing, recreation, as well as for connecting between public transport and daily commuting. This indicates that e-bike sharing is evolving into a practical and dependable mode of transportation for both leisure and non-leisure trips. He et al. (2019) employed Poisson regression to investigate the factors influencing e-bike sharing utilization. Their findings revealed that proximity to public transportation hubs, recreational centers, and the density of bikeways all positively impact e-bike use. As e-bike sharing emerges as a prevalent shared service, it is increasingly employed for daily commuting, with its use being influenced by factors like the availability of dedicated cycle paths and the distance from recreational and other facilities.

The above-mentioned studies have primarily focused on exploring the spatiotemporal travel patterns and the influencing factors of bike sharing and e-bike sharing individually. However, to enhance user services and assist operators in fleet allocation more efficiently, it is essential to conduct a comparative analysis of the spatiotemporal travel patterns and influencing factors between bike sharing and e-bike sharing systems. This study aims to fill this gap by first comparing and analysis their spatiotemporal travel patterns, assessed through metrics such as travel distance, travel time, and travel volume. Several potential influencing factors, including land use types and public transport facilities, have been gathered from multiple data sources. Additionally, to pinpoint the factors that exhibit significant influence, we employ covariance and spatial autocorrelation analysis methods. Subsequently, these identified influential factors are incorporated into the MGWR model, enabling a quantitative examination of their impact on the spatiotemporal travel patterns of both bike sharing and e-bike sharing systems. This comparative analysis aims to provide valuable insights that can inform service improvements and fleet management strategies for both bike sharing and e-bike sharing systems, contributing to more efficient and user-friendly shared mobility options.

The rest of the paper is organized as follows. Section 2 describes the study area and dataset utilized in this study. In Section 3, the research methods are presented. Section 4 discusses and analyzes the results of the spatiotemporal travel patterns and influencing factors for bike sharing and e-bike sharing, and compares the performance of the Geographically Weighted Regression (GWR) and MGWR models. Section 5 provides a summary of the main findings as well as the future work.

2. STUDY AREA AND DATA

2.1 Study area

This research was conducted within the study area of Manhattan, New York City, USA. Manhattan serves as the central district of New York City and renowned for its high population density, encompassing a total area of 87.5 km^2. As of 2019, the resident population of Manhattan was estimated to be approximately 1.63 million, as reported by the U.S. Census Bureau. Manhattan boasts a robust and well-developed transportation infrastructure, offering a diverse range of transportation modes, including private cars, buses, subways, taxis, private bicycles, bike sharing, and pedestrian pathways. In a dedicated effort to enhance the convenience and overall travel experience for its residents, New York City introduced a pioneering shared mobility service program named CitiBike in May 2013. CitiBike stands as the largest shared mobility program in the United States, featuring an extensive network of 658 stations and approximately 6,000 bicycles strategically distributed throughout the borough of Manhattan.

2.2 Study data

The data used in this study was sourced from the CitiBike website (https://citibikenyc.com/system-data). The website provides access to a comprehensive dataset containing CitiBike ride information for each month starting from the launch of operations in July 2013. This dataset includes crucial details such as vehicle identification number, vehicle type (classic bike or e-bike), ride start and end times, origin and destination station information, user classification (member or casual rider), station names, and the corresponding latitude and longitude coordinates for both the starting and ending stations. For the purposes of this research, we obtained and utilized the ride data for the month of May 2022 from the CitiBike website (https://citibikenyc.com/system-data) as the primary dataset for our study. To ensure the reliability and accuracy of the dataset, the bike sharing and e-bike sharing data underwent a series of preprocessing steps, as described below:

1.Orders that start or end outside the study area were deleted.
2.Orders with a ride time of less than 2 minutes were deleted.
3.Orders with a ride time greater than 120 minutes were deleted.
4.Orders with a trip distance of 0 were deleted.

After the pre-processing steps, we obtained 1,852,892 pieces pf eligible CitiBike records, which include 1,385,577 bike sharing orders and 467,315 e-bike sharing orders. The order data covers 658 stations in the Manhattan area.

In this study, we conducted an analysis to investigate the factors influencing the spatial and temporal travel patterns of both bike sharing and e-bike sharing. These factors encompassed two categories: land use and public transportation. The land use factor was evaluated using POI data, while the public transportation factor was assessed using data pertaining to subway stations and bus stops. These datasets were acquired from the New York City Open Data Platform (https://opendata.cityofnewyork.us/). To facilitate our geospatial analysis, we utilized census areas obtained from the U.S. Census Bureau (https://www.census.gov/). These census areas subdivided the Manhattan region into 288 Traffic Analysis Zones (TAZs) based on street blocks. The distribution of CitiBike stations and TAZs in the Manhattan area of New York, USA, is visually depicted in Figure 1.

Figure 1. Distribution of CitiBike stations and TAZs in the Manhattan area of New York, US.

3. METHODOLOGY

The main aim of this study is to conduct a comparative analysis of the spatiotemporal travel patterns and the influencing factors of bike sharing and e-bike sharing services. We employ multiple covariance and spatial autocorrelation analyses to identify the factors that exert a substantial impact on travel volume. Subsequently, these influential factors are integrated into the MGWR model to quantitatively assess their effects on the spatiotemporal travel patterns of both bike sharing and e-bike sharing systems. The overall framework of this study is depicted in Figure 2.

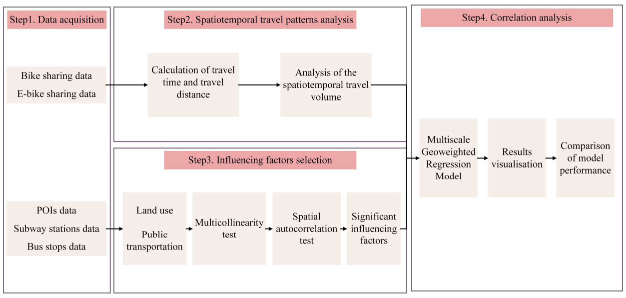

Figure 2. An overall framework for conducting this study

3.1 Multicollinearity test

Multicollinearity is a condition where independent variables in a multiple regression model exhibit some level of linear dependence, potentially introducing bias into the interpretation of the significance and effects of other independent variables. This can lead to unstable and unreliable analytical results. To address and manage the potential issues arising from multicollinearity, this study utilized the Variance Inflation Factor (VIF) as a diagnostic tool to evaluate the extent of multicollinearity. The VIF measures the degree of multicollinearity among independent variables in a regression model. Higher VIF values indicate a more pronounced degree of multicollinearity among the independent variables. By employing the VIF, we can identify and quantify the extent to which multicollinearity may be affecting our analysis, allowing us to take appropriate corrective actions as needed.

3.2 Spatial autocorrelation test

The most commonly used technique for analysing spatial variability is the Moran's I test (Ni and Chen, 2020). Before building the MGWR model, it evaluates the spatial autocorrelation of each independent variable and can help in evaluating the strength and type of spatial self-correlation of each independent variable, allowing the proper spatial weight matrix to be chosen.

Moran's I values range from -1 to 1, where a positive value indicates a positive correlation between the variable of interest, and larger values imply more significant spatial correlation. Conversely, a negative value indicates a negative correlation, and smaller values signify greater spatial variability. A value of 0 implies that the variable of interest is randomly distributed in space (Moran, 1950).

3.3 MGWR model

Anselin (1988) discovered that ordinary least square (OLS) models were always the starting point of spatial regression analysis, but OLS models were unable to disclose the spatial relationships between bike sharing and influential factor variables. The GWR model was proposed as an extension of the global linear regression model, which can investigate the heterogeneity of geospatial variables (Brunsdon et al., 1998). The GWR model can also be used to investigate non-stationarity, where variables vary in relation to one another based on geographic location. In addressing the non-stationarity of geospatial relationships, GWR models have been demonstrated to be preferable to global regression models.

While the GWR model has found extensive application in addressing spatial non-stationarity issues, it does have a notable limitation. Specifically, it employs a single global average bandwidth for all variables to define the range of influence for each variable. This approach overlooks the variation in the magnitude of influence among different variables, potentially introducing bias into the estimation results of the GWR model. To overcome this limitation, the MGWR model is introduced, offering a superior alternative to the GWR model. The MGWR model represents an enhancement and refinement of the GWR methodology. Notably, it provides an optimized bandwidth for each independent variable. This optimization ensures that the model takes into account the unique spatial influence characteristics of each variable, leading to more accurate and reliable estimation results compared to the GWR model. The MGWR model is calculated as follows (Brunsdon et al., 2002),

$$y_i = \beta_0(u_i,v_i) + \sum_{j=0}^{k} \beta_{bwj}(u_i,v_i)x_{ij} + \varepsilon_i \,, \tag{1}$$

where y_i is the attribute value at position i ; β_{bwj} is the bandwidth of the j_th variable defining the regression coefficient; $\beta_0(u_i,v_i)$ is the central coordinate at position i;$\beta_{bwj}(u_i,v_i)$ is the regression coefficient of the j_th variable at position i; and $\beta_0(u_i,v_i)$ and ε_i are the intercept and error term of the model at position i, respectively.

3.4 Evaluation

In this study, we evaluated the performance of the MGWR model by comparing it with the GWR model using two classical metrics: the Adjusted R^2 and the value of AICc. The Adjusted R^2 metric eliminates the effect of the number of independent variables on the R^2, making it possible to compare the goodness of fit of different models. The formula to calculate the Adjusted R^2 is as follows:

$$AdjustedR^2 = 1 - \left[\frac{(1-R^2)(n-1)}{(n-k-1)}\right] \,, \tag{2}$$

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where n denotes the number of samples; k denotes the number of independent variables. In addition to Adjusted R^2, AICc is a common metric used to evaluate models. A smaller value of AICc indicates an optimal choice of model. the formula for calculating AICc is as follows:

$$AICc=2n\log_e\left(\frac{RSS}{n}\right)+n\log_e(2\pi)+n\frac{n+tr(S)}{n-2-tr(S)}\ , \tag{3}$$

where n is the number of observations, S is the influence or hat matrix, and RSS is the residual sum of square.

4. RESULTS AND DISCUSSION

In this section, we conducted an analysis of the spatiotemporal characteristics and factors that influence the usage of bike sharing and e-bike sharing systems. In section 4.1.1, we examined and analyzed the travel distance and travel time of bike sharing and e-bike sharing; In section 4.1.2, we analyzed the spatiotemporal travel volume of bike sharing and e-bike sharing. In section 4.2, we visualised the correlation coefficients of the independent variables for the MGWR model. Finally, the performance of the MGWR model and the GWR model were compared.

4.1 Comparison of spatiotemporal travel patterns

4.1.1 Travel distance and travel time

By analysing the orders for bike sharing and e-bike sharing, we found that the average travel distance (Manhattan distance (He et al., 2018)) and average travel time for bike sharing were 1.790 kilometres and 13.9 minutes, respectively. For e-bike sharing, the average travel distance and travel time were slightly higher, namely 2.140 kilometers and 14.2 minutes, respectively. Figure 3. shows the distribution of travel distances for bike sharing and e-bike sharing. The figure shows that 33.45% of bike sharing trips and 24.9% of e-bike sharing trips had a travel distance between 0-1 kilometeres. For travel distances between 1-2 kilometers, the distribution for the two types of services was 35.1% and 34.79% respectively. However, for travel distance exceeding 2 kilometres, the proportion of users utilizing e-bikes was significantly higher than that of bike sharing. Conversely, the proportion of bike sharing was higher than that of e-bike sharing for travel distances less than 2 kilometers. This phenomenon can be attributed to the popularity of bike sharing for trips within 2 kilometers, as people can reach their destinations in less than 30 minutes. As shown in Figure4, 48.26% of bike sharing trips and 48.74% of e-bike sharing trips had a ride time of less than 10 minutes. Furthermore, more than 90% of rides in both sharing systems were completed within 30 minutes. This pattern can be attributed to the pricing policies in place. Bike sharing users are allowed a free ride for up to 30 minutes, while e-bike sharing users are charged from the beginning of the ride and face higher fees for trips lasting longer than 30 minutes. As a result, the majority of both bike sharing and e-bike sharing rides fall within the 30-minute timeframe.

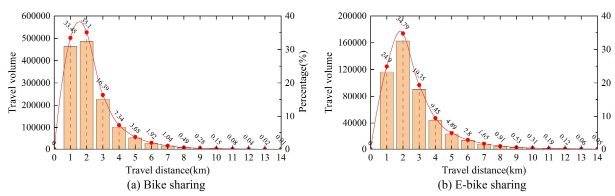

Figure 3. Distribution of travel distance of bike sharing and e-bike sharing systems.

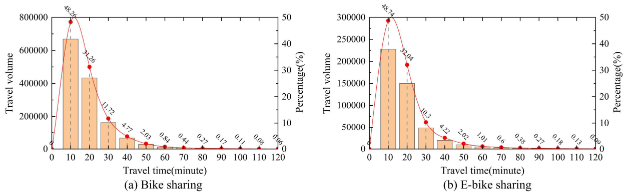

Figure 4. Distribution of travel time of bike sharing and e-bike sharing systems.

4.1.2 Travel volume

Figure 5. show the hourly travel volume of bike sharing and e-bike sharing during the week. The data reveals that bike sharing had the highest travel volume of 28,859 trips per hour, whereas e-bike sharing had a lower peak travel volume of 8,737 trips per hour. Both bike sharing and e-bike sharing exhibit notable peaks in usage on weekdays, with the highest travel volumes occurring during the morning and afternoon rush hours. Specifically, the peak periods for bike sharing were observed from 7:00 to 9:00, while for e-bike sharing, the peak periods were from 17:00 to 19:00. These findings suggest that these services are primarily utilized for commuting purposes during weekdays, aligning with previous research (Mateo-Babiano et al., 2016; Shen et al., 2018). Additionally, during non-commuting peak hours, the number of bike sharing trips exceeded that of e-bike sharing trips, indicating that bike sharing serves as not only a commuting mode but also plays a significant role in other daily activities (Wang et al., 2019). On weekends, both bike sharing and e-bike sharing experienced peak usage, with Sundays exhibiting significantly higher trip volumes compared to Saturdays.

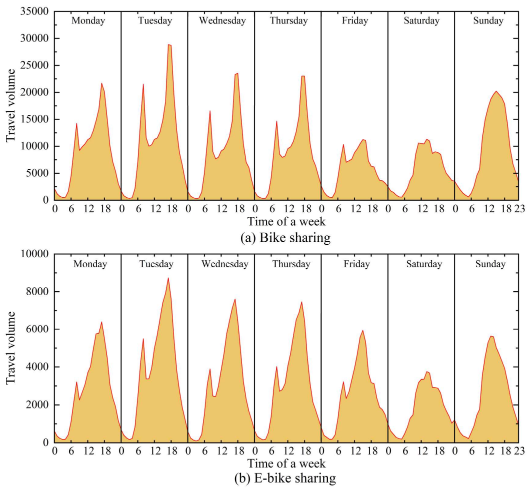

Figure 5. Distribution of hourly travel volume of bike and e-bike sharing systems in a week.

The analysis of temporal usage patterns of bike sharing and e-bike sharing reveals that both systems exhibit the highest travel volumes during the morning and evening peak hours on weekdays. To further investigate their spatial differences in usage, this study focused on the weekday morning and afternoon peak hours as the study periods and visualized the average hourly travel volume for both systems using Manhattan TAZs data, as depicted in Figure 6. The visualization illustrates that bike sharing and e-bike sharing trips consistently had higher travel volumes in Southwest Manhattan compared to Northeast Manhattan. This discrepancy can be attributed to the concentration of commercial and financial facilities in Southwest Manhattan, which likely drives the usage of shared services in that area. Furthermore, Central Park, a renowned tourist destination, exhibits higher travel volumes for both shared services during the weekday morning and evening rush hours. This can be attributed to the popularity of the Central Park South Loop, which is a highly frequented bike riding route in New York City and is completely closed to car traffic. These factors contribute to the promotion of shared services usage in this area.

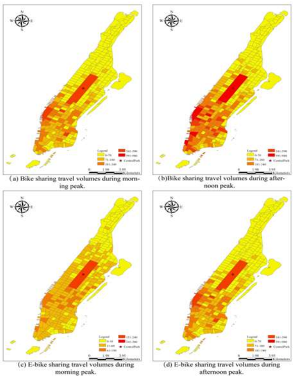

Figure 6. Spatial distribution of hourly travel volumes for bike and e-bike sharing in the morning and afternoon peaks.

4.2 MGWR correlation analysis results

In order to investigate the factors that drive the different spatiotemporal travel patterns, we first selected 14 independent variables, e.g., the number of residential facilities, educational facilities, recreational facilities, subway stops, and bus stops, which were generated from POIs data, subway station data, and bus stop data. Those variables with the VIF-value >10 and P-value > 0.05 were excluded through computing multiple covariance and spatial autocorrelation analysis (Pan et al., 2020; Calvo et al., 2019). The remaining variables are presented in Table 1.

In this study we selected three variables with lower VIF values, namely the number of educational facilities, cultural facilities and bus stops, indicating they had more significant impact on the spatiotemporal travel patterns. In addition, we further conducted a correlation analysis based on the MGWR model and plotted a visualisation of the correlation coefficients for each variable. Figure 7. shows the impact of educational facilities on the travel volume of bike sharing and e-bike sharing systems in each TAZ on weekdays and weekends. Educational facilities had a negative impact on the travel volume of bike sharing in the North East region and e-bike sharing in the Central region, where the negative impact was smaller on weekdays than on weekends. The reason for this may be that educational facilities are more disperse in the North East regions, where people mostly travelling by school bus on weekdays but not working on weekends, thus have a more pronounced negative impact on the shared system.

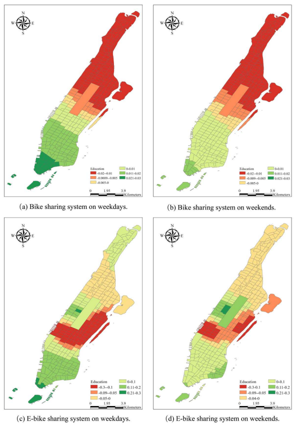

Figure 7. The impact of educational facilities on bike sharing and e-bike sharing system during weekdays and weekends.

Table 1. Results of VIF and Moran's I.

Variable types	Variable	VIF	Moran's I	Z-score	P-value
Land use	# Residential facilities	1.395	0.174	7.115	0.001
	# Educational facilities	1.078	0.125	5.131	0.001
	# Cultural facilities	1.491	0.246	9.992	0.001
	# Social service facilities	1.475	0.077	3.207	0.005
	#Transportation facilities	2.087	0.068	2.883	0.011
	# Commercial facilities	1.727	0.459	18.551	0.001
	# Government facilities	1.038	0.279	11.326	0.001
	# Religious institutions	1.090	0.205	8.348	0.001
Public transport	# Subway stations	1.325	0.108	4.453	0.003
	# Bus stops	1.164	0.109	4.489	0.001

Note: "#" indicates the number.

Figure 8. shows the impact of cultural facilities on the travel volume of bike sharing and e-bike sharing systems in each TAZ on weekdays and weekends. Cultural facilities had a negative impact on bike sharing in the Central Region and on e-bike sharing throughout Manhattan, where the negative impact was smaller on weekends than on weekdays. The reasons for this may be that cultural facilities are more densely distributed in the Midlands, that people can reach any cultural facility without relying on shared services, and that people have more time to engage in cultural activities on weekends than on weekdays.

Figure 9. shows the impact of bus stops on the travel volume of bike sharing and e-bike sharing systems in each TAZ on weekdays and weekends. Bus stops had a significant negative impact on bike sharing and e-bike sharing at Chelsea Waterside Park, which is only present on weekdays. The bus stops showed a positive impact on both during the weekends, and a more significant positive impact on e-bike sharing than on bike sharing. The reason for this may be that on weekdays people are less likely to visit Chelsea Waterside Park, which have a negative impact on the shared service, while on weekends people have more time to

play and will choose the ease and speed of e-bike sharing as a means of transport.

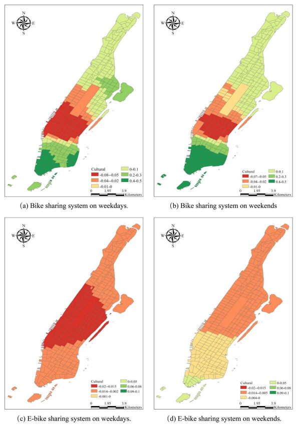

Figure 8. The impact of educational facilities on bike sharing and e-bike sharing systems during weekdays and weekends.

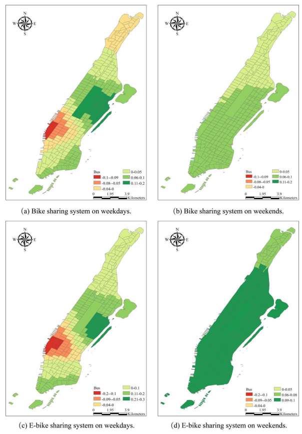

Figure 9. The impact of bus stops on bike sharing and e-bike sharing system during weekdays and weekends.

Furthermore, aiming at better evaluating the performance of the MGWR model, we conducted a comparison experiment with the GWR model using two metrics, i.e., Adjusted R^2 and AICc. Table 2. shows that the MGWR model had a larger Adjusted R^2 and a smaller AICc than the GWR model, indicating that MGWR is more effective for conducting the correlation analysis to quantitatively explain the impact of different factors on spatiotemporal travel patterns.

5. CONCLUSIONS AND FUTURE WORK

The integration of bike sharing and e-bike sharing systems presents an opportunity to enhance sustainable transportation. To optimize the provision of shared services, it is essential to compare the spatial and temporal travel characteristics and influencing factors of both systems. This study pioneers the use of multiple sources of data to compare the spatiotemporal travel patterns and the influencing factors of bike sharing and e-bike sharing.

This paper compares the spatiotemporal travel patterns and the influencing factors of bike sharing and e-bike sharing. Firstly, the order data of the two systems is compared and analysed for measuring the spatiotemporal travel patterns composed by travel distance, travel time, and travel volume. Then, the MGWR model was constructed to explore the influence of land use and public transportation factors on the volume of travel in the two systems, and the coefficients of the three selected variables, namely educational facilities, cultural facilities and bus stops, were visualised and analysed. The study found that for bike sharing, educational facilities had a significant negative impact on the travel volume of bike sharing, both on weekdays and weekends, while the opposite was true for cultural facilities and bus stops. For e-bike sharing, bus stops had a significant positive impact on e-bike sharing travel volumes, both on weekdays and weekends, while cultural facilities reflected a significant negative impact. Finally, the MGWR model was compared with the GWR model and the results showed that the MGWR model was superior to the GWR model with regard to performing correlation analysis to quantitatively explain the effect of different factors on spatiotemporal travel patterns.

Table 2. Comparative results of GWR and MGWR models.

	Bike sharing				E-bike sharing			
	Weekday		Weekend		Weekday		Weekend	
	Adjusted R^2	AICc	Adjusted R^2	AICc	Adjusted R^2	AICc	Adjusted R^2	AICc
GWR	0.607	623.505	0.639	608.942	0.616	630.954	0.631	615.038
MGWR	0.624	586.137	0.671	559.427	0.633	607.119	0.637	580.502

Despite those achievements made in this study, there still exists several limitations that can be taken into consideration in the future. Different user groups (e.g., gender, age groups, commuters and non-commuters) at finer scales (e.g., weekday morning rush hours and weekday evening rush hours) as well as more factors such as temperature, weather, and socio-demographic characteristics can be further analyzed to help better understand the spatiotemporal travel patterns and the influencing factors of bike sharing and e-bike sharing systems. The study sheds light on the urban planning of shared services, optimising the allocation of bike sharing and e-bike sharing.

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