Decoding the Spatial Heterogeneity of Bike-Sharing Impacts: Machine Learning Model of Meteorology, Epidemic, and Urban Factors

Jiawei Yao, Ph.D.[1]; Yixin Jian[2]; Yanting Shen[3]; Wen Wen[4]; Chenyu Huang, Ph.D.[5]; Jinyu Wang[6]; Jiayan Fu[7]; Zhongqi Yu, Ph.D.[8]; and Yecheng Zhang, Ph.D.[9]

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Abstract: Previous studies on the factors affecting bike-sharing travel (BST) have not considered spatial differences, leading to insufficient understanding of the complex impacts of variables in different geographical locations. This study aims to reveal the differential spatial impacts of meteorological conditions, epidemics, and urban spatial variables on BST. Firstly, New York was selected as the study area, and the period from 2020 to 2021 was chosen for the study. Secondly, a high-precision urban information data set, including meteorological, epidemic, and urban spatial variables, was constructed using weighted Thiessen polygons as the segmentation method. Finally, machine learning was conducted, and the XGBoost ensemble learning algorithm, which yielded the best training results, was chosen for interpretable analysis. This examined the nonlinear correlations and spatial benefits of each variable with BST. The results show that (1) the impact of average temperature on shared bicycle travel is most significant among all factors, accounting for 26.15% of the total impact; (2) there is significant spatial heterogeneity in the influence of factors, and office closeness is negatively correlated with BST, contributing positively in the west and negatively in the east; (3) the southern part of Manhattan is significantly affected by meteorological (|SHAP value| = 484.18) and urban spatial sector (|SHAP value| = 122.65), while the central part of Manhattan is most significantly influenced by epidemic variables (|SHAP value| = 469.27). In summary, this study takes New York as an example to analyze the nonlinear effects and spatial benefits of meteorology, epidemics, and urban space on shared bicycle travel. Based on this, more targeted and effective urban traffic intervention strategies are provided for different regions of the city. **DOI:** 10.1061/JUPDDM.UPENG-5192. *© 2025 American Society of Civil Engineers*.

Practical Applications: This study provides valuable insights into how different factors influence bike-sharing travel in New York City, offering practical implications for urban planners and policymakers. Firstly, we found that temperature has the most significant impact on bike-sharing, highlighting the necessity for climate-conscious dynamic urban planning. Secondly, our research reveals that the effects of meteorological, epidemic, and urban space factors vary greatly across different regions. The study identifies that the areas most sensitive to these factors are in Midtown and Lower Manhattan, which should be prioritized for interventions. Additionally, southern Manhattan is significantly affected by meteorology and urban space factors, while central Manhattan is more influenced by the number of confirmed COVID-19 cases. This underscores the importance of targeted policies. In southern Manhattan, measures such as improving the microclimate through street shading and increasing the accessibility of public and commercial spaces can encourage bike-sharing. Conversely, in central Manhattan, monitoring epidemic trends and managing the number of cases is crucial. By considering the spatial differences in factors affecting bike-sharing travel, cities can develop more effective, region-specific transportation strategies, ultimately enhancing urban resilience and reducing the impact of epidemics.

Author keywords: Meteorology; Epidemics; Urban space; Interpretable analysis; Spatial benefits.

[1]Associate Professor, College of Architecture and Urban Planning, Tongji Univ., Shanghai 200092, China; Anhui Province Key Laboratory of Intelligent Building & Building Energy Saving, Anhui Jianzhu Univ., Hefei 230022, China. Email: jiawei.yao@tongji.edu.cn

[2]College of Architecture and Urban Planning, Tongji Univ., Shanghai 200092, China. ORCID: https://orcid.org/0009-0009-9384-8492. Email: yixin_jian@tongji.edu.cn

[3]College of Architecture and Urban Planning, Tongji Univ., Shanghai 200092, China. Email: sytsyt188@163.com

[4]Consulting & Planning Branch, Chengdu Design Consulting Group, Chengdu 610000, China. Email: wenw@tju.edu.cn

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[5]College of Architecture and Urban Planning, Tongji Univ., Shanghai 200092, China. ORCID: https://orcid.org/0000-0002-6360-638X. Email: cyhuang@tongji.edu.cn

[6]College of Architecture and Urban Planning, Tongji Univ., Shanghai 200092, China. ORCID: https://orcid.org/0009-0004-1287-5864. Email: johnwang1998@163.com

[7]Postdoctoral Fellow, College of Architecture and Urban Planning, Tongji Univ., Shanghai 200092, China. ORCID: https://orcid.org/0009-0009-5411-1826. Email: fujiayan@tongji.edu.cn

[8]Assistant Professor, College of Architecture and Urban Planning, Tongji Univ., Shanghai 200092, China; Tongji Architectural Design (Group) Co., Ltd., Shanghai 200092 China (corresponding author). Email: yzq_caup@tongji.edu.cn

[9]School of Architecture, Tsinghua Univ., Beijing 100084, China. ORCID: https://orcid.org/0000-0002-4151-2737. Email: zhangyec23@mails.tsinghua.edu.cn

Introduction

Factors such as climate and social changes, as well as sustainable urban development issues, have increasingly made green transportation solutions such as bike-sharing more favorable (Shaheen et al. 2010). Additionally, bike-sharing plays a significant role in maintaining health and physical activity levels (Arellana et al. 2020). However, bike-sharing faces challenges of temporal and spatial demand fluctuations, exhibiting complex nonlinear patterns (Cao and Wang 2022). During the COVID-19 pandemic, public health considerations led governments to restrict the use of centralized public transportation systems, making bike-sharing a primary alternative mode of transportation. The use and frequency of bike-sharing changed significantly compared with previous periods, reflecting its impact. The pandemic experience has shown that bike-sharing systems have great potential to enhance the resilience of urban transportation systems in disruptive events (Li and Lasenby 2023). Focusing on the overall impact mechanisms of bike-sharing travel (BST) can significantly improve urban resilience in the postpandemic era. Existing studies, often based on traditional statistical regression methods or conventional machine learning, tend to lack flexibility in dealing with nonlinear relationships and complex patterns, failing to focus on the local effects of features and unable to analyze the spatial fluctuations of feature impacts. This study aims to reveal the spatial effect differences and nonlinear impacts of meteorological, epidemic, and urban spatial factors on BST through interpretable machine learning, providing significant guidance for urban transportation planning in the postpandemic era.

Literature Review

There has been extensive research on the impact of epidemics on BST. Generally, cycling activities increased during the pandemic compared with nonpandemic periods (Buehler and Pucher 2023). The level of cycling varied across different stages of the pandemic. In the United States, for example, there was an average increase of 3% in cycling levels during the entire pandemic period of 2019–2021, with a 16% increase from 2019 to 2020 and a 13% decrease from 2020 to 2021. Bi et al. (2022) used 18 months of BSS data for a joint analysis of bike-sharing spatial mobility and network connectivity, finding increased usage near supermarkets, parks, and hospitals during the outbreak, with significant declines in other areas. Kim and Cho (2022) employed the Panel Vector Autoregression model to simulate the relationship between cycling and public transportation in Seoul before and after the pandemic, demonstrating that bike-sharing diverted some subway traffic during COVID-19, enhancing the overall resilience of urban transportation systems. Research by multiple scholars indicated that during the COVID-19 pandemic, bike-sharing was used more for long-distance leisure trips rather than for work-related travel or short trips to or from public transportation (Chen et al. 2022; Li and Zhao 2022; Xin et al. 2022). The outbreak of COVID-19 also expanded the scale of bike-sharing in cities like New York and Vancouver, accelerating the addition and implementation of infrastructure such as bike lanes (Buehler and Pucher 2022). These studies demonstrate the impact of the pandemic on bike-sharing, but due to their reliance on traditional statistical methods, they have not accurately obtained the specific characteristics of individual bike use during the pandemic, nor fully revealed the spatial effects of pandemic features on bike use.

In addition to the impact of epidemic factors during special periods, BST has long been significantly affected by meteorological factors. Weather is one of the most prominent factors influencing cycling rates, in addition to terrain, infrastructure, land-use combinations, calendar events, and peak periods (An et al. 2019). Firstly, the impact of weather depends on the geographical environment. In warmer regions, such as Brisbane, Corcoran et al. (2014) explored the impact of weather and special events on the spatiotemporal distribution of bike-sharing using the Poisson regression model, finding that high temperatures had a significant positive effect, while rainfall and high wind speeds had negative impacts. In colder regions, Faghih-Imani et al. (2014), using public operational data from Montreal in 2012 and a mixed linear model, found a positive correlation between bike-sharing usage and temperature, and a negative correlation with humidity. Precipitation and snowfall were also found to have a sustained negative impact on passenger volume (El-Assi et al. 2017; Shen et al. 2018). Secondly, on a finer temporal scale, studies have shown that cycling is most likely to be affected by weather conditions in spring, and least likely in winter. Additionally, weekend cycling is less affected by weather, while weekday cycling activities are more influenced (Zhao et al. 2018). These studies indicate that weather conditions affect cycling patterns and must be considered when researching the spatial effects and nonlinear patterns of BST during the pandemic.

Bike-sharing passenger volume and usage patterns are also significantly influenced by land-use and built environment attributes (Zhao et al. 2018). Previous research has explored the impact of various urban indicators on traffic flow from a macrourban perspective. In terms of land use, diverse land uses increase bike-sharing usage (El-Assi et al. 2017; Shen et al. 2018). Shen et al. (2018) used a spatial autoregressive model and found that land-use combinations have a positive impact on bike-sharing. Additionally, the demand for bike-sharing seems to be influenced by the presence and proximity of transportation infrastructure (Hossain et al. 2024). For instance, studies by Garrard et al. (2008) and Berrigan et al. (2010) found a direct correlation between road connectivity and infrastructure and residents' choices of cycling routes. These studies have assisted in the selection of urban spatial impact factors for this research, but have not yet characterized the spatial effects and nonlinear impacts of individual factors on BST.

In terms of research methodology, due to the stringent inferential framework in geospatial research, traditional spatial statistical models, such as spatial econometric models (including spatial lag and error models) and spatial variance coefficient models (including geographically weighted regression), are usually more favored by researchers for their local explanatory capabilities. Some studies, using New York's CitiBike bike-sharing system as the subject, have employed panel spatial lag and spatial error models to examine bike-sharing demand, revealing significant spatiotemporal interactions (Faghih-Imani and Eluru 2016); others have used panel mixed multinomial logit models for multivariate analysis, identifying factors affecting travel time differences (Faghih-Imani et al. 2017). In recent years, machine learning methods, due to their powerful high-dimensional data processing capabilities, accurate predictive performance, flexibility, adaptability, and generalization ability, have been widely promoted and popularized, with many studies utilizing machine learning methods to propose new research workflows or summarize new conclusions. Traditionally, research on bike-sharing demand has focused on prediction through regression methods, but these models often overlooked the impact of modifiable spatial unit problems. Sun and Lu's (2023) research addressed this issue, proposing a diversified machine learning method for spatial interpolation fusion, estimating the relative roles of different land-use types in bike-sharing demand. Peláez-Rodríguez et al. (2024) used 12 different multivariate regression techniques, covering everything from machine learning methods to time series deep learning methods, to solve bike-sharing flow prediction

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problems and extract global conclusions about multivariate feature correlations. Moreover, local interpretability methods, such as SHAP, have also been proven capable of extracting spatial effects from spatial data machine learning models (Li 2022). Therefore, machine learning methods can compensate for the shortcomings of traditional spatial statistical models in the transportation field, uncovering more complex mechanisms and the interrelationships among multiple variables.

Methods

This study chose New York City as the research object, exploring the changes in human mobility under COVID-19. Firstly, the data source and research location were determined and then the research period was classified and defined based on statistical results. Then, weighted Thiessen polygons were employed in the buffer zone control study to extract epidemic, meteorological, and urban spatial variables from nonoverlapping service areas, determining key indicators included in the machine learning model. Subsequently, a multivariate machine learning model was established based on geostatistical interpolation calibration and spatial statistics. The XGBoost algorithm, noted for its optimal performance, was selected as an example. The spatial effects of various factors were inferred and visualized by plotting the corresponding location's SHAP values. Finally, the study's conclusions, recommendations, limitations, and potential future research directions were discussed. Fig. 1 presents the overall framework of the research.

Research Area and Period

This study selects New York City as the research area, with the study period spanning from November 1, 2020 to February 28, 2021.

Citi Bike, New York City's bike-sharing service, is the largest of its kind in the United States. Since its launch in 2013, it has expanded to become an essential part of New York City's transportation infrastructure. Additionally, New York City, being the most populous city in the United States, was significantly impacted during the COVID-19 pandemic. Given the absence of bike stations in the Bronx and Staten Island, this study focuses on Manhattan, Brooklyn, and Queens, where bike stations are available. As shown in Fig. 2, the number of confirmed cases in areas covered by bike stations fluctuated greatly and was unevenly distributed. This suggests that subsequent analyses might reveal differences in how varying degrees of pandemic severity influenced cycling behavior. To maintain clarity, avoid potential confusion and double counting between start and return trips, and ensure that the data remain concise and easy to interpret; this study exclusively considers trips based on their start locations. Fig. 3 illustrates the changes and distribution in the number of BST based on start locations during the study period. Although there was a slight decline in the total number of BST during this period, the overall number of trips stabilized toward the end.

The bike-sharing system is more resilient and better able to withstand unexpected events compared with the subway system (Teixeira and Lopes 2020; Cao and Wang 2022). Studies have shown that in the context of COVID-19, bike-sharing serves as an excellent outdoor activity for individuals to maintain health and prevent virus transmission, effectively responding to health crises (Rotaris et al. 2022; Sung 2023). It plays a significant role in maintaining physical activity levels and reducing the risk of obesity and mental health issues (Arellana et al. 2020; Kroesen 2014; Teixeira and Lopes 2020; Oestreich et al. 2023). Bike-sharing has been proven to effectively support public health and reduce the risk of COVID-19 transmission (Fuller et al. 2021; Musselwhite et al. 2020; Irawan et al. 2023). Government agencies have explicitly promoted cycling as a solution to mitigate the spread of COVID-19, with Paris and the Philippines serving as notable examples (Buehler and Pucher 2023), aiming to minimize the risk of COVID-19 transmission (Tirachini and Cats 2020). Existing research has thoroughly explored BST patterns and influencing factors across different phases: prepandemic, during the pandemic, and postpandemic (Shi et al. 2023), during the lockdown period (before May 2020) (Padmanabhan et al. 2021; Li et al. 2021), and during the gradual reopening period (before August 2020) (Hu et al. 2021; Song et al. 2022; Doubleday et al. 2021). This study focuses on the fluctuations during the relatively underresearched stable pandemic period from November 1, 2020, to February 28, 2021. This period represents a peak of fluctuations in the normalized phase of the pandemic following the reduction of restrictive policies. The patterns observed during this time are representative and can help us fully leverage the resilience of the bike-sharing system to reduce epidemic levels. This is highly significant for the current era of the postpandemic new normal. Fig. 4 shows the changes in the number of COVID-19 cases during the study period.

Data Collection

The study built a machine learning predictive model for BST volumes based on three key indicators: meteorological factors, epidemic factors, and urban spatial factors. Table 1 details the data sources for the study.

For meteorological factors, the study selected six indicators: average temperature, wind speed, average precipitation, total precipitation, average minimum temperature, and average maximum temperature. With regard to epidemic changes, the study intersected each bike-sharing station's coverage area with New York City's MODZCTA data, processing data on COVID-19 infection rates and BST at different times to obtain epidemiological variables. For urban spatial factors, urban network analysis was introduced, integrating the gravity index of urban spatial-type facilities into the Thiessen scale. Then, the Kriging method was used for interpolation and calibration of epidemic, meteorological, and urban spatial elements, providing standardized variables for machine learning modeling. According to the detailed rules of building type classification in New York, land use can be divided into factories, commercial, apartment, office, public, and transportation. Analytical indices generated from space syntax, including gravity, betweenness, closeness, and straightness, served as spatial data sources. The calculation methods for urban spatial indicators are listed subsequently.

Gravity Index (Gra) captures the cumulative accessibility of a residential zone to job opportunities in different employment zones, considering the travel impedance (time) between them. Gra could be calculated by using the following equation:

$$\mathrm{Gra} = \sum_{j} \mathrm{Jobs}_j \times \sqrt[v]{\mathrm{Time}_{ij}} \tag{1}$$

Jobs_j = number of jobs in employment zone j; v = gamma coefficient, representing travelers' sensitivity to travel time; and Time_{ij} = network travel time between residential zone i and employment zone j.

Betweenness Index (Bet) measures how often a node is traversed by the shortest paths connecting all pairs of nodes in the network. Bet could be calculated by using the following equation:

$$\mathrm{Bet} = \frac{1}{(N-1)(N-2)} \sum_{j=1;k=1;j\neq k\neq i}^{N} \frac{n_{jk}(i)}{n_{jk}} \tag{2}$$

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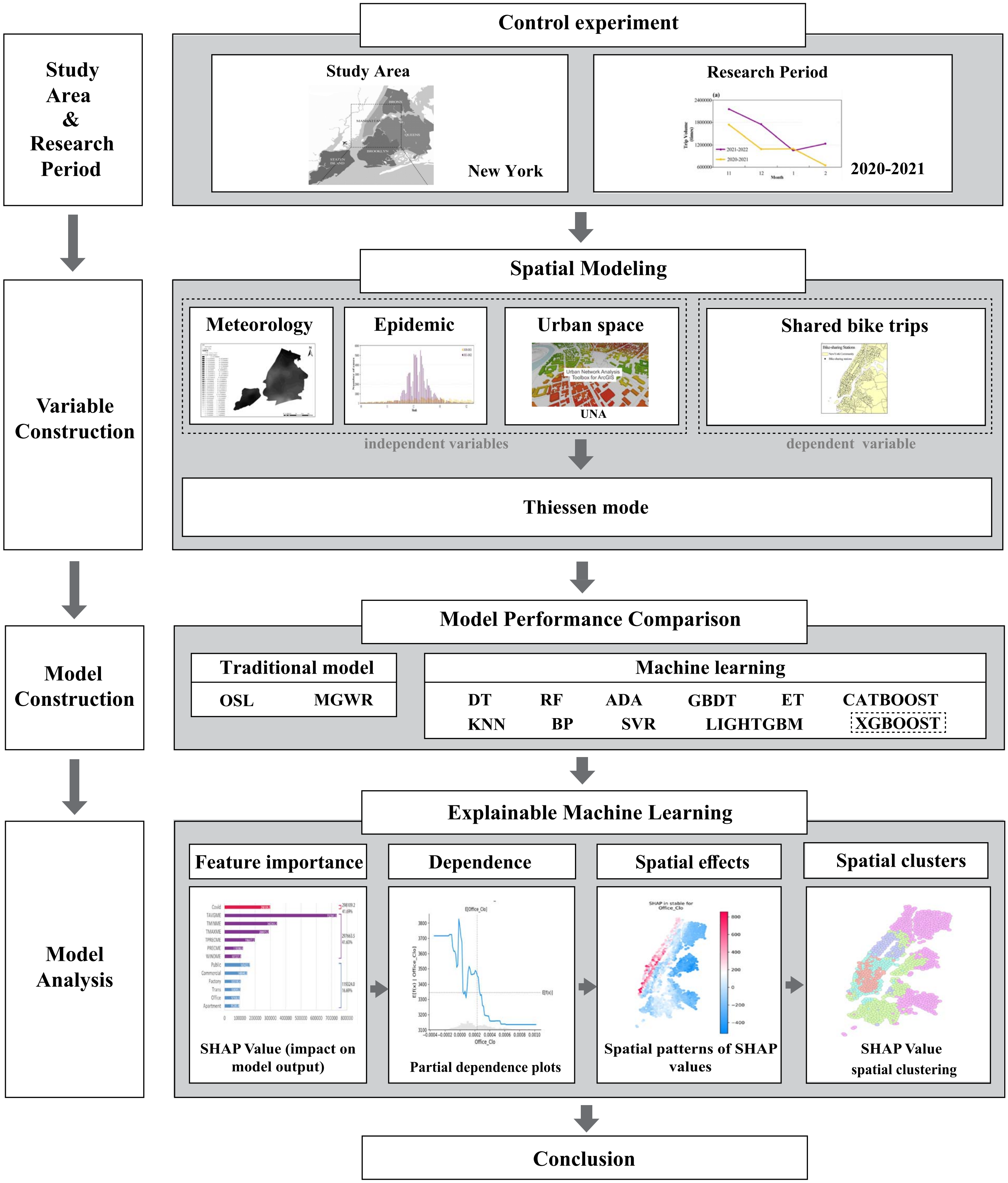

Fig. 1. Framework. (Maps reprinted from GADM 2022.)

where N = total number of nodes in the network; n_{jk} = number of shortest paths between nodes j and k; and $n_{jk}(i)$ = number of these shortest paths that contain node i.

Closeness Index (Clo) measures how close a node is to all the other nodes along the shortest paths of the network. Clo could be calculated by using the following equation:

$$\mathrm{Clo} = \frac{N-1}{\sum_{j=1;j\neq i}^{N} d_{ij}} \tag{3}$$

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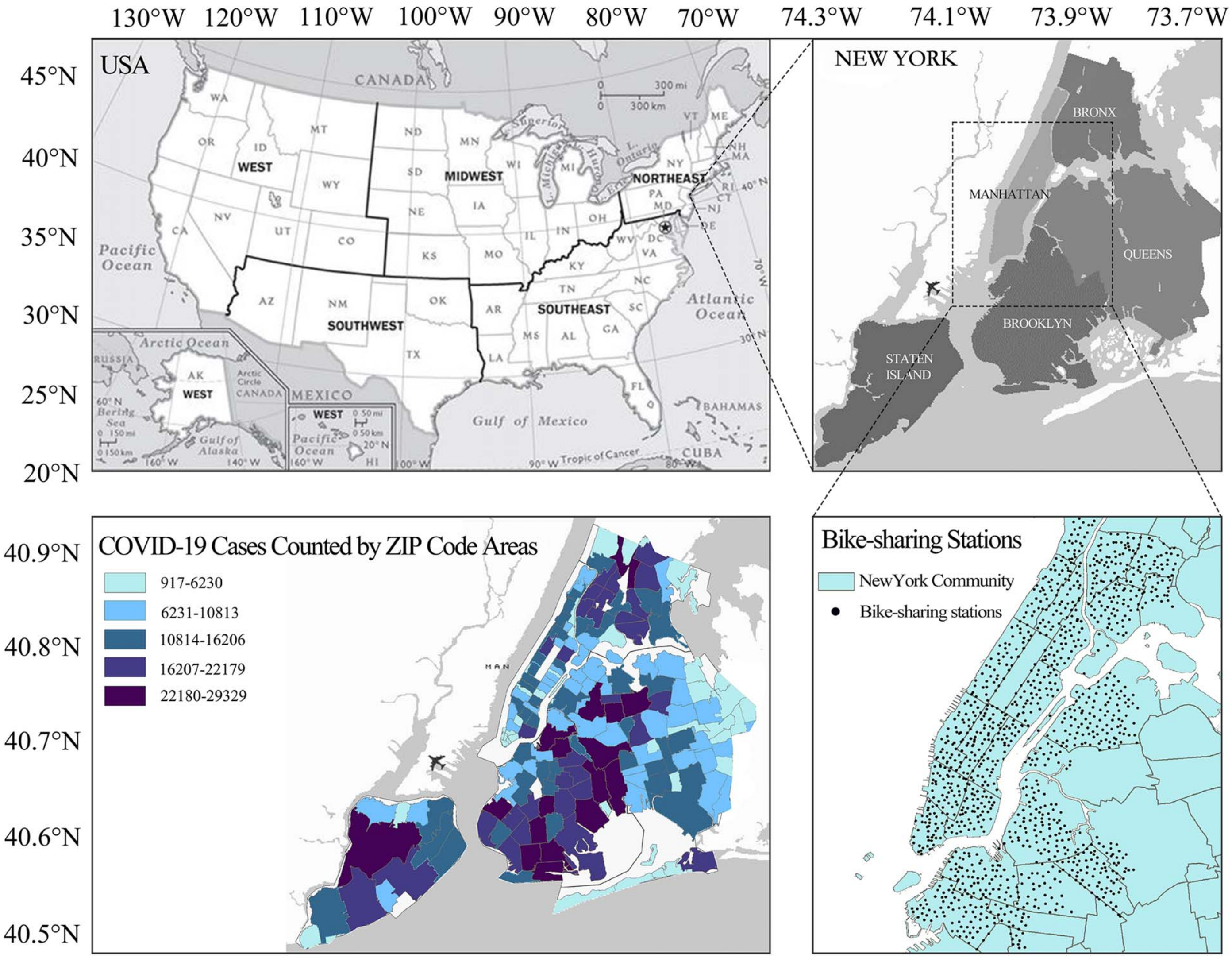

Fig. 2. Study Area. (Maps reprinted from GADM 2022.)

d_{ij} = shortest distance between nodes i and j. In other words, Clo is the inverse of average distance from this node to all other nodes.

Straightness Index (Str) measures how much the shortest paths from a node to all others deviate from the virtual straight lines (Euclidean distances) connecting them. Str could be calculated by using the following equation:

$$\mathrm{Str} = \frac{1}{N-1} \sum_{j=i;j\neq i}^{N} \frac{d_{ij}^{\mathrm{Eucl}}}{d_{ij}} \tag{4}$$

d_{ij}^{Eucl} = Euclidean distance between nodes i and j.

The start and end points of BST based on docking stations are constrained by each station's location. Most related studies identified influencing factors within a certain radius around bike stations. However, existing research has shown that using Thiessen polygons can improve regression performance compared with using circular buffers alone (Wang et al. 2021). Moreover, from a pedestrian perspective, users tend to choose the nearest bike station to their origin or destination, disregarding the distance to other walkable stations. Choosing Thiessen polygons as the segmentation method ensures that each point within the service area is closest relative to all other stations. This study employed a Gaussian kernel density interpolation method, representing the aggregation degree of shared bike stations within urban space through a kernel function. After data normalization, map algebra, and other operations such as deriving a cost grid equation, the study area was divided into weighted Thiessen polygons, collecting various data types as listed in Table 1.

Model Construction and Comparison

Machine Learning Model

Traditional spatial models consider spatial specificity and correlation when processing geospatial data, which can reveal local or global geographic information. For instance, the multiscale geographically weighted regression (MGWR) model accounts for spatial heterogeneity, meaning different regression relationships may exist in different geographical locations, using various spatial weight matrices to adapt to spatial variations. This study uses traditional spatial models as a benchmark to examine whether interpretable machine learning models have better fitting accuracy and explanatory power. This validates the feasibility of applying machine learning in geospatial research.

Machine learning models are better at capturing and modeling nonlinear relationships compared with traditional spatial models. For complex geographical phenomena, especially those with nonlinear features, machine learning models can usually provide better fitting. The machine learning process is as follows: select

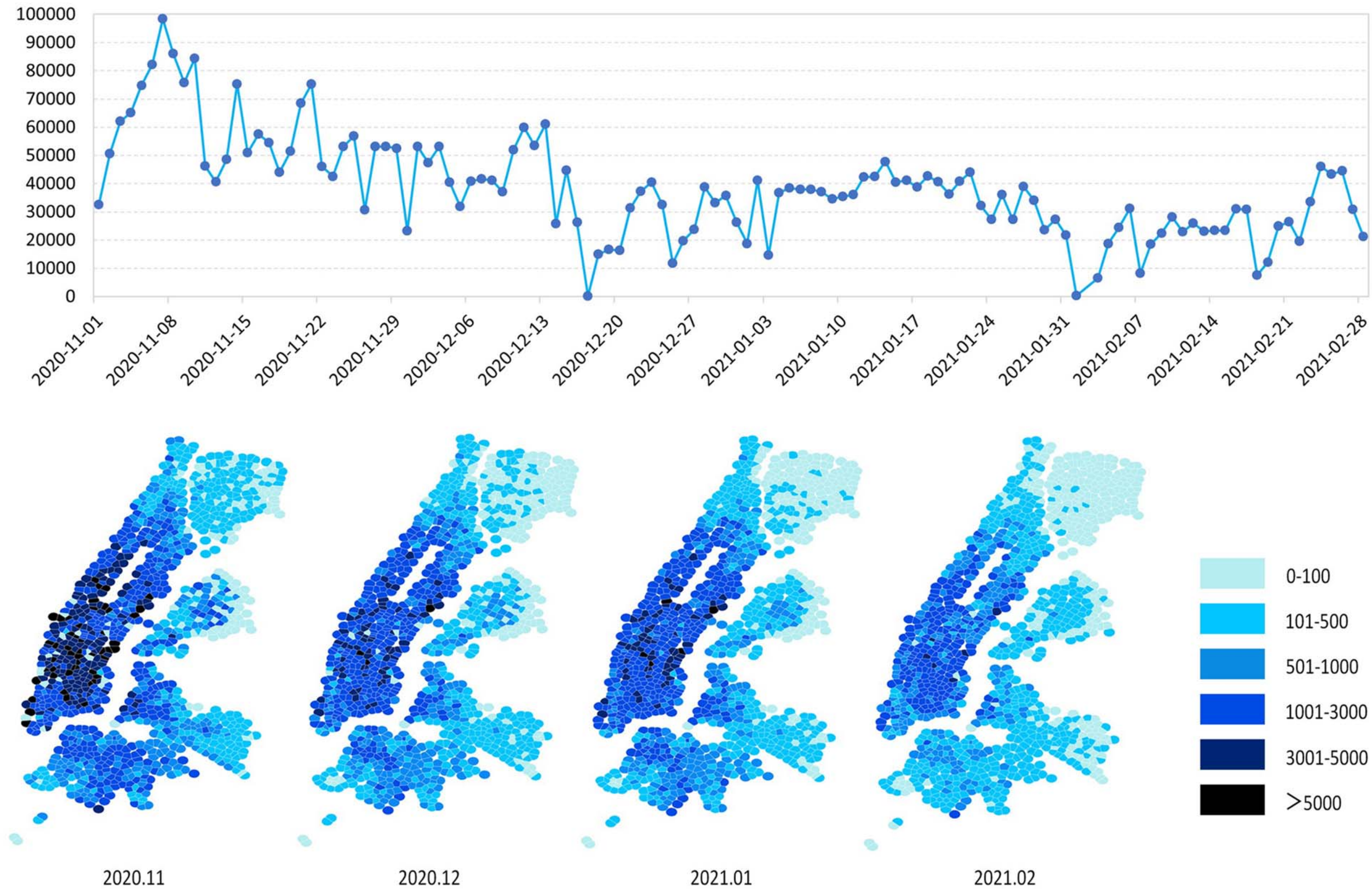

Fig. 3. Number of BSTs based on start locations.

initial $P < 0.05$ and exclude collinear indicators from machine learning modeling. After data standardization, perform three sigma outlier processing, exclude nonnormal distribution data, and split the data set in a 7:3 ratio. Regression is then conducted using classic machine learning algorithms such as DT (Decision Tree), RF (Random Forest), ADA (Adaboost), GBDT (Gradient Boosting Decision Tree), ET (Extra Trees), CATBOOST (Categorical Boosting), KNN (K-Nearest Neighbors), BP (Backpropagation), SVR (Support Vector Regression), XGBOOST (Extreme Gradient Boosting), LIGHTGBM (Light Gradient Boosting Machine) to fit bike travel volumes during stable and outbreak periods.

Interpretable Machine Learning

Traditional machine learning models cannot provide information about the impact of each feature on the model output. To deeply understand the model's sensitivity to different features, this study continues with the best-performing XGBoost model as

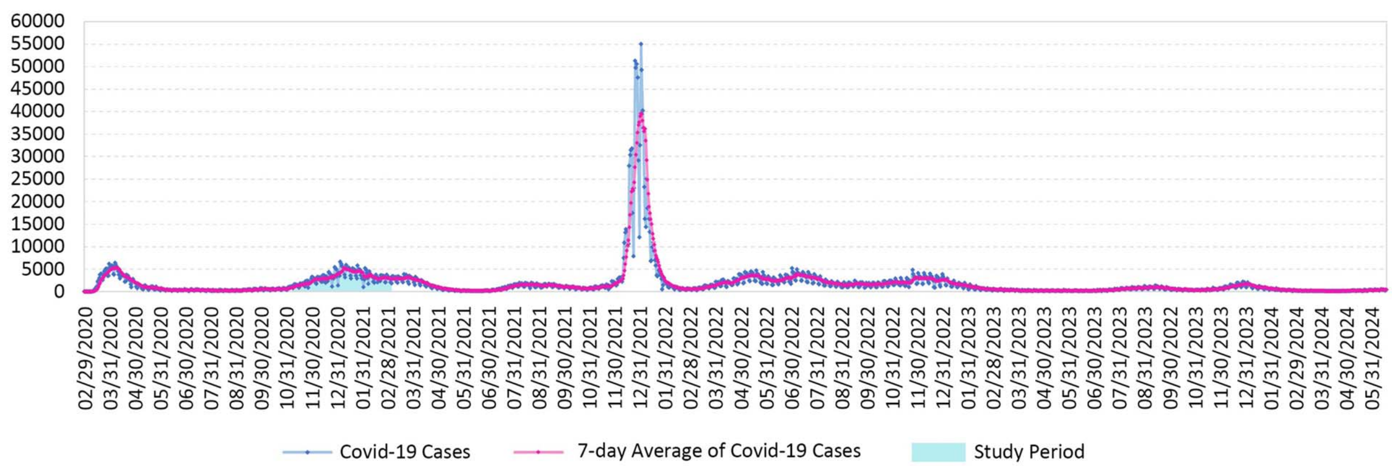

Fig. 4. Number of COVID-19 cases.

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an example, using the SHAP library in Python to calculate the model's SHAP values, thereby demonstrating the model's spatial effects. This method has been applied in various previous studies, demonstrating its feasibility (Shen et al. 2024). The SHAP values of spatial lag terms are calculated by the sum of the estimated SHAP values of geographical coordinates and the mean of the dependent variable.

For the XGBoost model, this study uses the Bayesian optimization package Hyperopt (Bergstra et al. 2013) for hyperparameter tuning with nested fivefold cross-validation. The final XGBoost model is trained on 70% of the entire data set and tested on an independent 30% test data to avoid overfitting.

The SHAP in interpretable analysis, originating from game theory (Shapley 1953), aims to fairly distribute contributions when players jointly achieve a specific outcome. SHAP values can be used in machine learning to quantify each feature's contribution in the model. However, game theory is the main barrier to the calculation and application of SHAP values. Using the SHAP value calculation method proposed by Lundberg and Lee (2017) is another way to estimate SHAP values. The main contribution of SHAP lies in generating local additive feature attributions, enhancing the potential of machine learning models to understand spatial data, because each observation is referenced by its geographical location, allowing any estimated feature attribute to be visualized in space. This study adopts the tree-based SHAP estimation method, which is faster than kernel-based operations and can display the spatial interaction effects of different features. To clearly illustrate how individual features affect the model's predictive outcome, the study employs a dependency plot approach.

Results and Discussion

Machine Learning Performance

This study compared the training results of various machine learning models, and Table 2 presents the metrics of each machine learning model's test set. The results show that the XGBoost algorithm excels in predicting BST, with an R^2 value of 0.74, indicating that the model can explain 74% of the data variability.

The study also compared the best-performing XGBoost in machine learning with traditional spatial geographic models, as given in Table 3. The results indicate that the XGBoost model stands out in these comparisons, with the highest R^2 value (0.739). These figures suggest that XGBoost is superior to other models in explaining data variability and predictive accuracy.

Interpretability of Machine Learning

Contribution Ranking

The results obtained from an interpretable analysis of shared bicycle travel volume are as follows: Fig. 5 is the SHAP summary plot of the predictive model, where three colors represent meteorology, epidemic, and urban space sectors, respectively. The value of each

Table 1. Data source

Variables	Data type	Data source	Data name
Independent variables	Meteorology	The research of Fick and Hijmans (2017) has established the weather geographic forecast data (2020–2050) of 1 km grid	TAVG [average temperature (°C)] WIND [wind speed (m s^{-1})] PREC [precipitation (mm)] TMIN [average minimum temperature (°C)] TMAX [average maximum temperature (°C)] TPREC [total precipitation (mm)]
	Epidemic	The epidemic data are COVID data of MODZCTA district statistics based on the zip code provided by the US Department of Health	PE (patients of epidemic in November 2020–Februaru 2021)
	Urban space	Accessibility of POI calculated by urban network analysis	FG (factory gravity) FS (factory straightness) FC (factory closeness) FB (factory betweenness) CG (commerce gravity) CS (commerce straightness) CC (commerce closeness) CB (commerce betweenness) AG (apartment gravity) AS (apartment straightness) AC (apartment closeness) AB (apartment betweenness) OG (office gravity) OS (office straightness) OC (office closeness) OB (office gravity betweenness) PG (public gravity) PS (public straightness) PC (public closeness) PB (public betweenness) TG (transport gravity) TS (transport straightness) TC (transport closeness) TB (transport betweenness)
Dependent variables	Bike-sharing travel	New York shared a data set	Shared bicycle travel over a period of time (BST)

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factor is the sum of the absolute values of SHAP contributions, representing the total contribution of that factor to BST.

As shown in Fig. 5, meteorology, epidemic, and urban space are all significant factors affecting urban BST. Firstly, the results indicate that even during the pandemic, temperature remains the most influential factor on the number of rides, far exceeding the impact of the number of confirmed cases. Within meteorology factors, there is considerable internal variation in contribution values. The ∑|SHAP value| for average temperature (TAVG) is 732,341.3, accounting for 26.15% of the total influence of all factors, which is much higher than other factors. This conclusion differs from the study by Wang and Noland (2021), which may be primarily due to the different study periods. Their research mainly focused on the period before September 2020, during which stay-at-home orders and phased reopening policies amplified the impact of epidemic factors on BST. This study, however, focuses on the fluctuating period of the pandemic post reopening, examining the patterns of BST and epidemic factors during the normalization phase. The internal ranking of contributions within the meteorology sector shows that the impact of various temperatures (TVAG, TMIN, and TMAX) is significantly greater than TPREC, and the impact of TPREC is greater than WIND. This result is consistent with the conclusions of An et al. (2019), indicating that the internal contribution ranking of meteorology sector to BST during pandemic fluctuations is consistent with the prepandemic period. Therefore, prepandemic research conclusions on the impact of meteorological variables on bike travel can also be applied during pandemic fluctuations. This means that meteorology is an important indicator affecting BST in any period. In urban transportation planning, meteorology must be considered first, and different bike-sharing station capacities should be set according to the meteorological characteristics of different areas. This is significant for both daily and special periods. Secondly, the ∑|SHAP value| for PE is 298,109.3, accounting for 10.65% of the total influence of all factors, ranking third after TAVG and TMIN. This indicates that even during the new normal phase of the pandemic, fluctuations in PE still have a significant impact on BST. This means that in the event of emergencies, the intervention and disruption of BST by epidemic and other emergencies still need to be given considerable attention. Lastly, among urban space factors, public and commercial land use have the most significant impact on bike-sharing, accounting for 5.91% and 5.29%, respectively, followed by industrial and transportation land use. Office and apartment land use have the least impact. This conclusion aligns with Noland et al. (2019), who also found that stations with a higher proportion of commercial and public buildings are more attractive to cyclists. This indicates that during the mixed period of the pandemic, leisure travel on nonworking days fluctuates more, while essential commuting on working days fluctuates less. It shows that the accessibility of public land use is the most significant urban space factor affecting bike-sharing, implying that road planning connecting public land use needs special attention.

Table 2. Evaluation of machine learning test set models

Thiessen calculation	MSE	RMSE	MAE	MAPE	Test R^2 (train R^2)
DT	6.6×10^6	2,567.5	1,435.7	394.2	0.363 (1.000)
RF	2.8×10^6	1,666.5	1,013.5	278.3	0.732 (0.942)
ADA	5.9×10^6	2,432.0	2,101.6	577.1	0.429 (0.571)
GBDT	3.2×10^6	1,796.8	1,118.2	307.0	0.688 (0.886)
ET	2.8×10^6	1,675.1	990.1	271.9	0.729 (1.000)
CATBOOST	2.9×10^6	1,698.2	1,025.3	281.5	0.721 (0.989)
KNN	6.2×10^6	2,487.9	1,678.5	460.9	0.402 (0.512)
BP	4.4×10^6	2,103.2	1,475.6	405.2	0.573 (0.425)
SVR	1.1×10^6	3,357.2	2,284.0	627.2	−0.09 (−0.139)
LIGHTGBM	3.4×10^6	1,836.3	1,146.5	314.8	0.674 (0.999)
XGBOOST	2.7×10^6	1,644.1	1,012.0	277.9	**0.739** (0.940)

Note: The bolded part represents the highest R^2 value in the test set.

Table 3. Overall model accuracy comparison between traditional models and XGBoost

Model	Global regression	MGWR	XGBoost
R^2	0.615	0.608	0.739

Nonlinear Relationships

Fig. 6 shows the partial dependence plots of factors with high contributions to BST during the epidemic fluctuation period.

The results show that among meteorology factors, TAVG is positively correlated with BST, suggesting that warmer weather encourages bike-sharing in New York City. This trend has also been observed in other studies on bike-sharing systems (Corcoran et al. 2014). Previous research by Heaney et al. (2019) found a robust threshold relationship between temperature and bike rides from June to September, with a positive correlation up to temperature thresholds of 25.8°C and 28.1°C, beyond which ridership declined. This study focuses on the cold season from November to February and also found a threshold relationship between temperature and ridership. When TAVG exceeds 2.7°C, an increase in temperature significantly encourages bike-sharing; before this threshold, the relationship remains stable. The conclusion of the temperature threshold effect supplements the seasonal patterns of shared bicycle usage in New York City. This suggests that under the influence of urban heat islands and global warming, if the frequency of severe weather events like heavy rain and strong winds does not increase significantly, bike-sharing usage in New York City might continue to rise during the autumn and winter seasons (Bean et al. 2021). Therefore, we suggest considering climate factors dynamically in urban transportation planning. This involves incorporating future climate changes into planning and dynamically deploying seasonal bike-sharing infrastructure, such as increasing services in favorable seasons and reducing capacity for maintenance during extreme temperatures, to meet travel demand while saving costs and reducing bike wear.

PE and BST show a generally negative correlation. When PE is between 175 and 250, and between 270 and 375, an increase in PE leads to a decrease in bike-sharing usage, consistent with findings by Padmanabhan et al. (2021). This can be explained by the increased fear of traveling as the severity of the epidemic intensifies, leading to a reduction in travel behavior. Additionally, choosing to travel by bicycle can help reduce the severity of the epidemic to some extent. Cycling, as an outdoor exercise, improves personal fitness and reduces the risk of virus infection in crowded, enclosed spaces, resulting in a negative correlation between bike-sharing usage and PE. However, when PE is between 250 and 270, an increase in PE corresponds with an increase in bike-sharing usage, resulting in a local peak. This may be due to some people switching from public transportation to bike-sharing (Drummond and Hasnine 2023), and it reflects an increase in environmentally conscious individuals seeking a healthier lifestyle (Park et al. 2023). Therefore, we suggest that for necessary travel amid epidemic fluctuation period, personal and nonenclosed modes of transportation like bike-sharing should be encouraged over buses and subways to enhance personal health and mitigate the severity of the epidemic.

The relationship between urban space factors and BST is relatively complex. During the epidemic fluctuation period, PS and

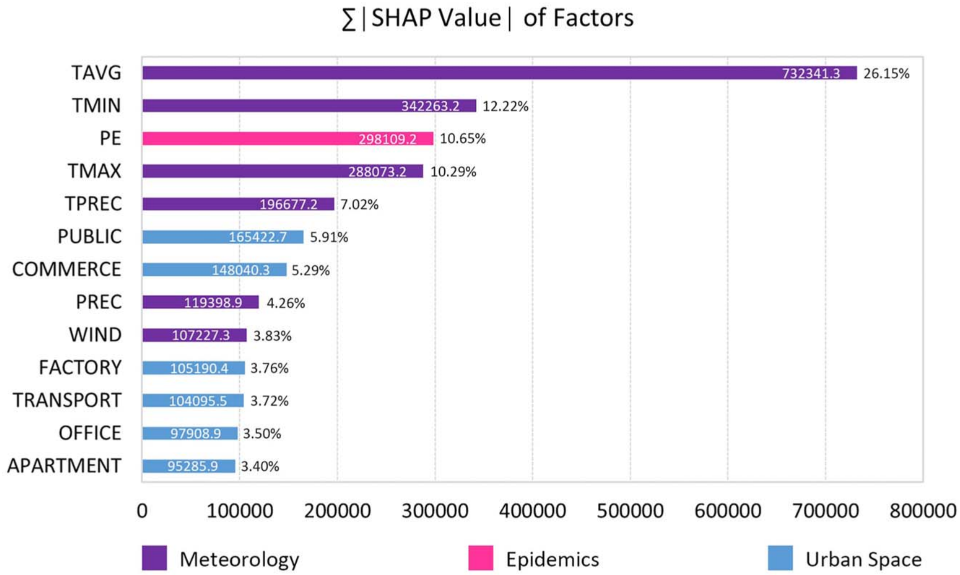

Fig. 5. SHAP summary plot of the predictive model.

AS shows a positive correlation with BST, indicating that for public and apartment land uses, more direct paths between POIs facilitate bike travel. TS shifts from a positive to a negative correlation with BST. This is because straightness measures how directly nodes in the network are connected via the shortest path, reflecting the directness of routes between nodes. When TS is <7.5, an increase in TS makes routes more efficient and convenient, which is more conducive to cycling, leading to an increase in BST. When TS exceeds 7.5, an increase in TS may indicate urban arterials lacking cycling facilities, leading cyclists to choose alternative routes for safety reasons (Pucher et al. 2010). A higher CB also encourages bike-sharing. When commercial land is located along the shortest paths between other nodes, its accessibility increases, making it easier to reach by bike.

The higher FG correlates with increased BST. This reflects that high density and efficiently connected industrial clusters are more suitable for frequent traffic flow, which can promote bike-sharing. This conclusion differs from Hu et al.'s (2021) findings on bike-sharing and land use in Singapore, likely due to differences in bike-sharing station distribution in different regions. In New York, bike-sharing stations do not significantly diminish around industrial areas, making concentrated industrial land favorable for commuting by bike. Additionally, the POI distribution of industrial land mainly in Brooklyn and Queens supports Drummond and Hasnine's (2023) conclusion. They found that Brooklyn, as a relatively low-income area, experienced a greater shift from public transportation to bike-sharing during the epidemic. This finding also corroborates the rationality of our conclusions. During the epidemic fluctuation period, office closeness (OC) and BST show a generally negative correlation with two peaks. This may be because when OC is too low, it indicates that office is close to other nodes, making travelers more likely to choose walking instead of cycling.

Spatial Patterns of SHAP Values

Consistent with previous research by Bi et al. (2022), this study also found significant spatial heterogeneity in the impact of meteorological, epidemic, and urban space factors on bike-sharing during the epidemic fluctuation period. Fig. 7 highlights the six most significant results of spatial influence for each factor. The results show that for all factors, the SHAP values on Manhattan Island are higher than in other areas outside Manhattan, such as the Bronx and eastern Queens. This may be due to the higher density of bike-sharing stations on Manhattan Island, leading to more data and more significant interaction effects. This conclusion aligns with the findings of Yang et al. (2020), Zhang et al. (2017), and Faghih-Imani et al. (2014), which observed that bike-sharing usage decreases with increasing distance from the CBD. TAVG and CB have the greatest contribution to the area between southern Manhattan and Midtown. This may be attributed to the strong residential nature of this area, where commercial land largely serves daily needs. Daily activities, such as shopping, are significantly influenced by temperature and the accessibility of commercial facilities, making it more convenient to reach these facilities when they are located along the shortest paths. PS has the greatest positive contribution to central and southern Manhattan and is the only factor that significantly positively influences bike-sharing in Brooklyn as well. This could be due to the higher density of public land POIs in these two regions. TPREC and PE have the most significant impact on the central area of Manhattan. This can be attributed to the fact that travel in this central area is primarily for leisure purposes, such as visiting Central Park, making it more susceptible to the impacts of rain and the severity of the epidemic. OC is calculated as the inverse of the total shortest path distance from one office to all other offices, describing the proximity of an office to all other offices in the network. The impact of OC on BST shows significant east–west differences. Along the strip on the west coast of Manhattan, OC has a positive effect on BST volume, suggesting that increasing the number of offices or reducing the distance between office nodes (thus increasing office density) is more conducive to increasing BST. However, in the east, the contribution is smaller, close to zero, and in more remote areas, even negative, indicating that a reduction in office nodes and density might, instead, promote BST growth. This pattern could be attributed to three factors. First, an examination of the distribution of office area POIs revealed that their distribution is uneven, and the sample size is relatively small. This is likely due to much of Manhattan being classified as mixed land use (Wang and Noland 2021), resulting in a significant lack of office area POIs. Consequently, during interpolation, certain areas lacking POIs were partially overlooked, which affected the calculation of the weighted distribution of the office proximity index. Based on the current POI distribution, the density on the west side of Manhattan is higher than on the east side, which amplifies

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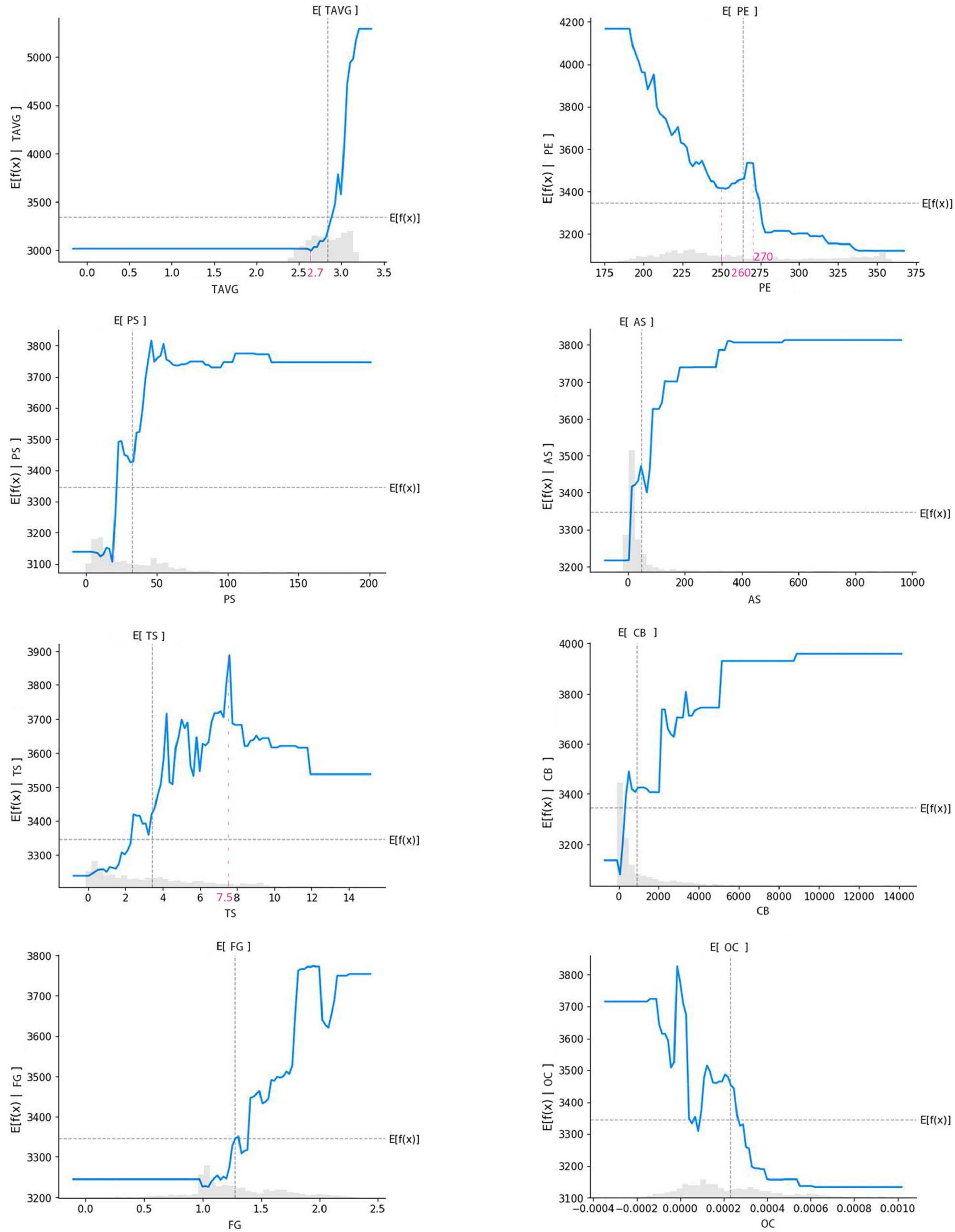

Fig. 6. Partial dependence plots.

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the substantial spatial differences in the impact of OC on BST between the two regions. This east–west heterogeneity aligns with New York City's zoning distribution, further demonstrating that cycling behavior is largely influenced by land-use types and associated activities. Zoning in West Manhattan shows an intermixing of residential and commercial office land, where residential areas mainly serve nearby office areas. Given this spatial structure, bike-sharing plays an important role in short-distance commuting in West Manhattan (Fishman 2015; Xu and Chow 2019), particularly when residential and workplace locations are relatively close. In contrast, the east side of Manhattan, along with the Bronx, Brooklyn, and Queens, is primarily residential, with limited commercial and office land. For cross-regional commuting, other modes of transportation are more likely to be utilized, while within these regions, bike-sharing trips are mainly for daily or community-related travel. Therefore, reducing office land use far from Manhattan and increasing community service land would be more conducive to the growth of BST in these areas. Secondly, the average road network density in West Manhattan (8.059×10^{-3}) is slightly lower than in the east (8.116×10^{-3}), yet significantly higher than in areas outside Manhattan (7.64×10^{-3}), which may be one of the key factors contributing to the east–west disparity in OC. The Superblocks Plan in Barcelona (Rueda 2019) and the Open Street Districts Plan in Shanghai further support this view. The former merged blocks and reduced streets for cars, expanding spaces for pedestrians and cyclists, while the latter removed community walls, enhancing the convenience of last-mile travel between communities and public transport. These urban cases demonstrate that overly low road network density can limit cycling efficiency, while overly high density may result in complex traffic environments and congestion. A

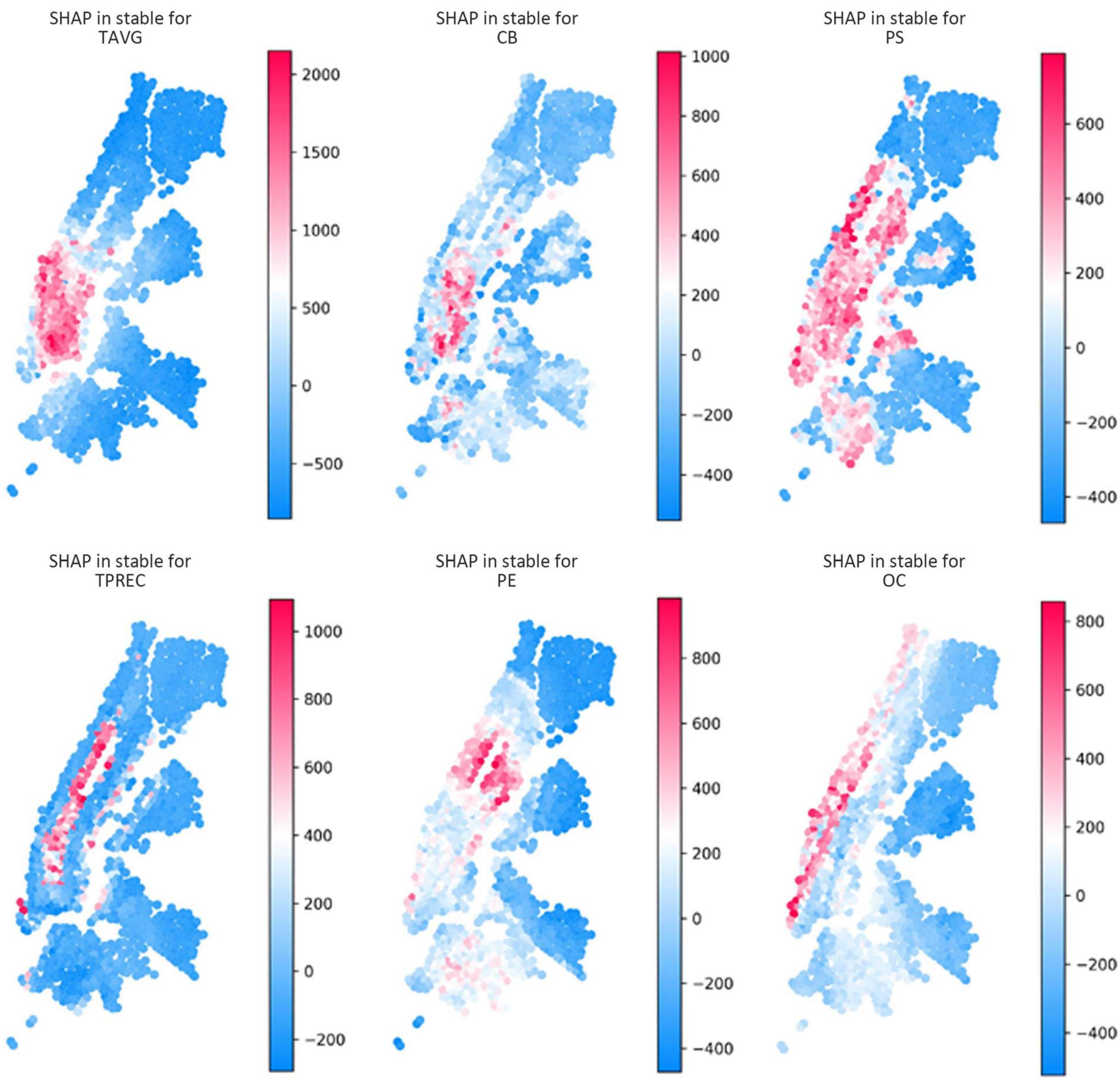

Fig. 7. Spatial distribution of SHAP values for each variable.

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balanced road network density can promote cycling development. Finally, this east–west difference may also be a result of shifts in mobility patterns caused by lockdown policies during the pandemic. Pase et al. (2020) found that, before the outbreak of COVID-19, cycling clusters were divided along an east–west axis spanning the island. After the outbreak, due to lockdown restrictions, user mobility shifted to a river-focused, north–south axis travel pattern.

Spatial Clustering of SHAP Values

By using the *k*-means algorithm, we clustered the SHAP values of 31 factors for each sample into five categories. This reveals the spatial patterns of the total contributions of various factors in different regions, as shown in Figs. 8(a and b) presents the average SHAP values of meteorological, epidemic, and urban space sectors within each cluster.

As seen in Fig. 8(a), for Manhattan Island during the pandemic fluctuation period, various factors generally have a positive impact on BST. Firstly, in the southern part of Manhattan, specifically Cluster 3, the total contribution of various factors to BST is the highest, reaching 195.39. This is largely attributed to the influence of three temperature factors: TAVG, TMIN, and TMAX. Previous studies have already concluded that TAVG is the most significant factor affecting BST, especially in the central and southern parts of Manhattan. This result also corroborates Tokey's (2020) finding that bike travel decreases more significantly near the CBD when overall bike usage declines, because this area is most affected by various factors. Secondly, in the Bronx, Queens, and Brooklyn, which are farther from Manhattan Island, the SHAP value is only 85.12, half that of southern Manhattan. This is likely due to the scarcity of bike-sharing stations and the overall lower travel volume in these areas, as well as the inconvenience of cycling due to insufficient cycling facilities. Therefore, if bike-sharing is to be encouraged in these regions, the first step should be to establish more bike-sharing stations and bike lanes to address the infrastructure deficiencies. Lastly, in the areas connecting Manhattan Island with the Bronx, Queens, and Brooklyn, the SHAP value further drops to just 30.89. This is likely because this area includes six transit points, which are essential for cross-regional movement and are less affected by various factors (Pucher et al. 2010). Additionally, travelers in this area may prefer other modes of transportation over long-distance cycling.

Fig. 8(b) shows two extreme values, which appear in Clusters 3 and 5. The impact of the meteorological sector is the greatest in Cluster 3, with an average SHAP value of 484.18, indicating that meteorology should be a key focus for BST in southern Manhattan. This may be determined by the function and the demographics of its residents. Cluster 3 is located between two CBDs, Midtown and Lower Manhattan, with residents primarily being white-collar professionals in these areas. Cycling behavior in this region is largely for daily commuting, in addition to routine shopping activities. Previous studies have found that weekday cycling is more affected by meteorology compared with weekend leisure cycling (Zhao et al. 2018). Therefore, the meteorological sector has the most significant impact on Cluster 3. This cluster also shows an extreme value for urban space sector, with an average SHAP value of 122.65, far exceeding the average SHAP values of urban space sector in other categories. This means that the impact on Cluster 3 is most significant when we perform the same level of renovation on urban space. The study by Xu and Chow (2019) supports this conclusion, finding that the boundary effect of infrastructure modifications in Manhattan (most samples are in the central and lower parts) from 2006 to 2016 was far greater than in other areas. The epidemic sector has the most significant impact in Cluster 5, meaning that the most important factor affecting BST in central Manhattan is PE. This is mainly due to the presence of Central Park. Studies have shown that BST near Central Park increased by about 200% during the pandemic, with a 237.6% increase in the usage rate of nearby bike stations (Bi et al. 2022).

The exploration of urban transportation patterns during the fluctuation period of the epidemic indicates that in practical applications, targeted policies and adjustments to urban resources must be implemented regionally and step by step. We recommend policymakers prioritize implementing measures to reform Cluster 3 in southern Manhattan, because the total contribution of various factors is the highest here. The most significant influence on Cluster 3 is from the meteorological sector, which depends more on natural environmental conditions and is difficult to control directly. However, urban microclimate can be regulated to increase BST by adjusting street shading, designing urban wind corridors, increasing greenery and water bodies, and predicting and monitoring outdoor comfort levels. Secondly, the role of urban space factors related to land use and street layout is significantly higher in Cluster 3 than in other clusters. Therefore, adjustments related to building functions and transportation planning should be piloted in southern

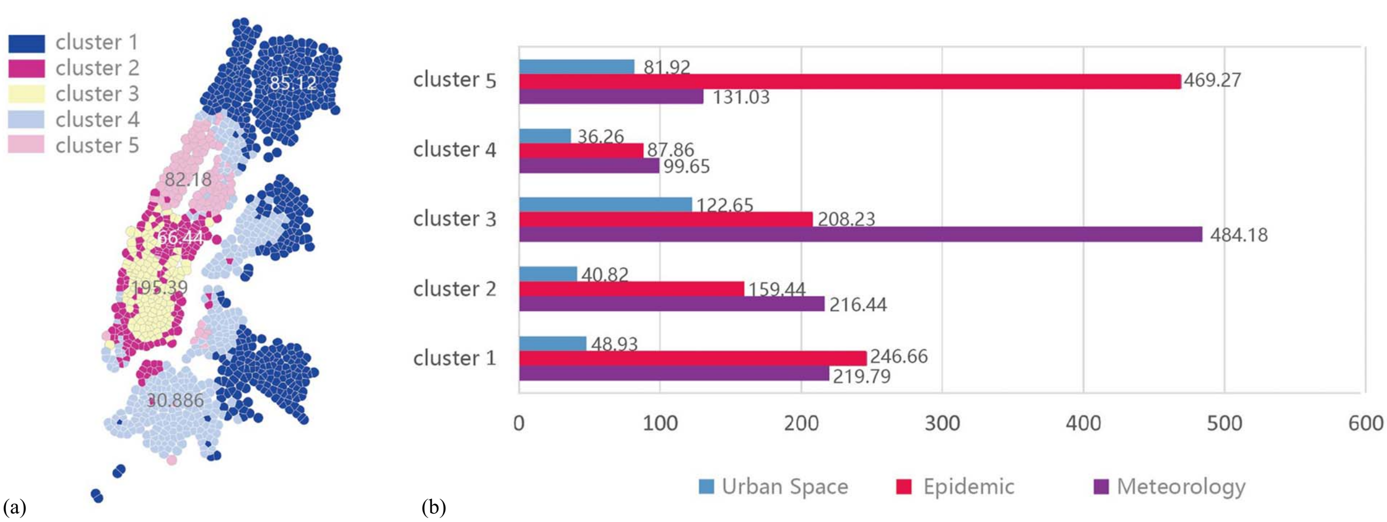

Fig. 8. Spatial clustering results: (a) spatial clustering results of SHAP values for various factors; and (b) average |SHAP value| within each cluster.

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Manhattan's Cluster 3. Based on the previous spatial pattern analysis, attention should be paid to the following aspects for Cluster 3:

1. Enhancing accessibility to public amenities by minimizing the distance between them and optimizing connecting roads. Public amenities such as medical facilities, exhibitions, government institutions, and parks should be placed along highly accessible routes, ideally near straight lines.
2. Placing commercial properties near junctions and intersections with other nodes to maximize connectivity.
3. Arranging office spaces in clusters to maintain minimal OC between them.

In addition, Cluster 5 exhibits extreme value related to the epidemic sector. This indicates that during the postpandemic new normal period, especially when the epidemic situation fluctuates, special attention should be given to the central Manhattan area near Central Park. PE in this area should be closely monitored and management strategies carefully considered. Additionally, by isolating the effects of other confounding variables, the severity of the epidemic can be estimated by inversely monitoring the usage of shared bicycles in this area.

Conclusions

In summary, this study used data-driven methods, machine learning, and interpretable analysis to analyze the nonlinear relationship and spatial distribution differences between meteorological factors, epidemic variables, urban spatial factors, and shared bicycle travel volume. This study utilized XGBOOST ensemble learning and SHAP interpretable analysis to provide a more in-depth mechanism analysis for the New York shared bicycle system.

This study has reached the following three main conclusions: First, during the pandemic fluctuation period, the impact of TAVG on BST is greater than that of the number of confirmed cases, with a contribution value of 732,341.3, accounting for 26.15%. Second, there is significant spatial heterogeneity in the impact of various factors. OC negatively correlates with BST, with notable differences in the east–west direction, contributing positively in the western coastal areas and negatively in the eastern areas. Third, the southern part of Manhattan is significantly affected by meteorology and urban space factors, with average |SHAP values| of 484.18 and 122.65, respectively. The central region is significantly affected by the epidemic factor, with an average |SHAP value| of 469.27. These findings provide valuable decision support for optimizing the layout of bike-sharing systems and improving urban transportation infrastructure. We recommend that urban policymakers implement region-specific and phased policies based on these conclusions. Specifically, renovation measures should first be applied to Cluster 3 in southern Manhattan. These measures include adjusting street shading, designing urban wind corridors, increasing greenery and water bodies, and predicting and monitoring outdoor space comfort to regulate the urban microclimate. Additionally, to encourage bike-sharing over enclosed transportation like subways, public land should be placed along highly accessible straight roads, commercial land near road intersections, and office spaces clustered together. These actions will enhance urban resilience and reduce epidemic levels.

Nevertheless, this study has certain limitations. First, the current selection of urban space variables only includes network analysis indicators, without considering more built environment variables such as building density and floor area ratio. Therefore, the strategic recommendations for urban space transformation may be incomplete. Second, a comparison of the average SHAP values between Manhattan and Queens reveals significant differences, indicating that BST is likely influenced by other determinants such as socioeconomic variables. This suggests that future studies exploring the mechanisms of BST should incorporate more socioeconomic and demographic variables, such as income, education, gender, diet, social structure, and neighborhood safety, to examine the correlation between these factors and BST from both subjective and objective perspectives. This would provide a more comprehensive understanding of the mechanisms underlying urban bike travel patterns (Babagoli et al. 2019; Willis et al. 2015). Additionally, because this study involves meteorological factors, it is inevitably influenced by the unique climatic characteristics of New York City, which may affect the generalizability of the conclusions. Therefore, future research should conduct more empirical studies in cities with different climatic conditions to validate the findings and enhance the generalizability of the study.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

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