

Article

Modelling Bottlenecks of Bike-Sharing Travel Using the Distinction between Endogenous and Exogenous Demand: A Case Study in Beijing

Sun Chao ^{1,2,3} and Lu Jian ^{1,2,3,*}

¹ Jiangsu Key Laboratory of Urban ITS, Southeast University, Nanjing 211189, China

² Jiangsu Province Collaborative Innovation Center of Modern Urban Traffic Technologies, Southeast University, Nanjing 211189, China

³ School of Transportation, Southeast University, Nanjing 211189, China

* Correspondence: lujian_1972@seu.edu.cn

Abstract: This paper aims to investigate the internal mechanisms of bottlenecks in bike-sharing travel. We perform kernel density analysis to obtain analysis points and areas designated by buffer areas. Additionally, we improve the spatial lag model through Tobit regression, so as to avoid the interference of autocorrelation and to set reasonable constraints for dependent variables. The proposed model distinguishes between bike-sharing demand determined by land use and other built environmental factors, which helps to define and identify bottlenecks in bike-sharing travel. Based on a Bayesian network fault tree, we define the diagnosis mode of evidence nodes to calculate the posterior probabilities and to determine the most sensitive factors for bottlenecks. We use Beijing city as the case study. The results show that the most sensitive factors that induce bottlenecks in bike-sharing travel are few subway stations, few bus stops, few bus lines, a low density of bike lanes, and more serious home–work separation. The findings presented here can enhance the generation of bike-sharing trips in response to bike-sharing development and contribute to adjusting the urban structure and reconstructing the green infrastructure layout.

Keywords: bike-sharing travel; bottlenecks; endogenous and exogenous demand; Bayesian network; fault tree



Citation: Chao, S.; Jian, L. Modelling Bottlenecks of Bike-Sharing Travel Using the Distinction between Endogenous and Exogenous Demand: A Case Study in Beijing. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 551. <https://doi.org/10.3390/ijgi11110551>

Academic Editors: Wolfgang Kainz and Jamal Jokar Arsanjani

Received: 31 July 2022

Accepted: 19 October 2022

Published: 8 November 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The combined mode of travel with bike-sharing as a significant part is a key element of traffic systems in large cities, especially in developing mobility as a service (MaaS) [1]. In fact, the emergence of bike-sharing has further reduced the time and space cost of activities and solved the connection problem within the last kilometer. Not surprisingly, over the past few years, it has also enhanced the attractiveness of other public transportation modes, such as subways, which is of great benefit to alleviate urban traffic congestion. In China, however, the popularization of bike-sharing has entered a difficult period. At present, the dispatching and managing scheme for bike-sharing is mainly a simple combination with other travel modes at the system level, ignoring spatial-temporal characteristics of urban travel behavior and other influencing factors at the micro-level. Unreasonable planning and control strategies will only increase the burden on cities. Apart from management issues, bike-sharing has also caused some spatial bottlenecks, which can then spread through the urban environment to other transportation infrastructures; obviously, there is less bike-sharing usage in some areas and cities. These bottlenecks are a large obstruction to bike-sharing advantages, but this obstruction is extremely difficult to understand, as it depends on land use and exogenous elements connected with natural, social, and built environmental factors. This raises the need to take into account these complicated effects when developing identification and elimination techniques for bottlenecks.

Generally, a bottleneck is defined as the key limiting factor of a whole process, which has different meanings in different fields. A production bottleneck refers to one or several factors that limit the overall level of workflow, including workflow completion time, workflow quality, and so on [2]. Broadly speaking, so-called bottlenecks actually amount to various factors restricting output in the whole process. In terms of traffic engineering, the link with the lowest traffic efficiency in a traffic network can be called a “bottleneck”, such as intersections and road segments with changing lanes [3]. Many comprehensive studies on traffic bottlenecks have put forward the weak points in improving transportation dominance and the service level. Thus, in order to enhance the attraction and usage of bike-sharing, we define the bottlenecks of bike-sharing travel as urban areas that are not conducive to bike-sharing dominance because of the differences in the built environmental.

Currently, there has been a rapid expansion of knowledge in the spatial and temporal characteristics of public bicycles, the influencing factors of bike-sharing behavior, the influencing factors of bike–rail transit connection behavior, and the influencing factors of bike–subway commuting behavior. In traffic engineering, large-scale data are dedicated to exploring the spatial and temporal behavior characteristics of shared traffic and put in place control and management of bike-sharing. Among these, one can employ clustering, regression, and so on to describe the travel modes for bike-sharing in different land use [4] and weather conditions [5]. Additionally, urban and transport planners are turning to environmental factors related to bike-sharing and bicycle–rail transit by relying on questionnaire sources to obtain travel choices [6]. This situation is a step forward in the explanation of dispatching strategies, which directly affect operations of the traffic system. In the context of data explosion, all of the studies on the travel characteristics and influencing factors of shared bikes, which stay up-to-date and have high popularity, have made important contributions to the development of transportation. However, a major limitation of the literature related to bike-sharing models is that researchers focus on one aspect based on correlation analysis, while ignoring comprehensive consideration of the environment. More importantly, although the fault theory has been commonly deployed to diagnose problems in the traffic system, little is known about the mechanism of bottleneck generation and diffusion that exists in bike-sharing travel. Therefore, the aim of this paper is to respond to the above-mentioned challenges by applying Bayesian causal networks with a fault tree and obtaining bike-sharing data and spatial data, so as to address the following research questions:

- ① Where are the bottlenecks of bike-sharing travel in a city? How can one find them by distinguishing between endogenous and exogenous demand?
- ② What are reasons for bottlenecks’ formation in bike-sharing travel? How can one determine the most key elements?

This paper is structured as follows. First, we summarize the related work on influencing factors for bike-sharing travel, as well as the development and application of traffic bottlenecks, in Section 2, based upon which we drew inspiration for our study. Section 3 discusses the methodologies followed to model bottlenecks of bike-sharing travel. Among them, we use hotspot detection with kernel density analysis to establish analysis areas in order to reach our goals and we describe that the land use that has been considered to generate travel demand differs from other environmental elements. In addition, we elaborate on the framework of using the Bayesian causal network with a fault tree model to analyze the generation mechanism and key driving factors of bike-sharing travel bottlenecks. Next, Section 4 presents the description of study area and data. Finally, we demonstrate the fitting results of the bottlenecks model in Section 5. This paper ends with the discussion and conclusions in Section 6.

2. Literature Review

In this section, we present research work that serves as a basis and inspiration for developing our bottleneck model, the mechanism performed in the model, and the study of complex hidden influencing factors.

2.1. Influencing Factors on Bike-Sharing Travel

The influencing factors of bike-sharing can be divided into two categories: time and space. Taking time as the control variable, we focus on the typical modes of shared travel [7]. For example, although the distribution of smaller bike-sharing systems is uncertain, the duration has been proved to be normally distributed in large bike-sharing systems [8]. This is because bike-sharing, as an auxiliary means of transportation, has a high correlation with time [9]. This representation of the temporal fluctuations analyzes the differentiation in bike-sharing travel demand between working days and non-working days, between holidays and non-holidays, and between morning and evening peak hours [10]. Compared with weekends, bike-sharing travel on workdays is more frequent, especially in the morning and evening peak hours [11,12]. In terms of a single day, the largest share of bike-sharing trips often occurs during the afternoon peak hour [13]. Additionally, weather related to time factors actually plays a fundamental role in bike-sharing ridership [14]. For instance, the temperature usually has a different influence during the different time periods within a day, which leads to a non-linear relationship between it and daily bike-sharing usage [15]. Then, daily usage may also vary according to rainfall, snowfall, and wind speed, but these rules may not apply to areas close to colleges and universities [16]. Sometimes, when choosing bike-sharing travel, cyclists tend to focus on the potential risk of the weather, such as PM 2.5 health exposure of bike-sharing cyclists [17].

During the bike-sharing modeling process, built land-use types are usually used to balance the required demand and supply. The built-up land use type indicates the relationship between potential travel demand and locations for a bike-sharing dispatching. This enables the bike-sharing management system (BSMS) and dispatching to transform the time-optimal target into a spatially optimal distribution. In this way, we consider the interaction mechanism between land-use and bike-sharing travel demand. Although the identification of land-use characteristics using bicycle sharing is also a very important application [18], at present, most of the research is mainly focused on describing the bike-sharing travel demand by land-use. Generally, as we are further away from the CBD (central business district), bike flow is expected to decrease, suggesting that accessibility measures seem to correlate with bike-sharing usage at each location [19]. Tighter, denser, flat, more continuous, and more recreational off-street bicycle networks in the CBD are also part of the reason for the higher mileage of bicycle travel (MBT) [20]. More importantly, the poor bicycle network in the suburbs puts vulnerable road users (such as cyclists) at high risk of injury, which makes many road users reluctant to ride bicycles [21]. Therefore, compared with land use, the conception of the built environment (BUE) may be more accurate, which entails considering comprehensive physical, geographical, and socioeconomic factors during the different models' spatial analysis phases as a bike-sharing management strategy [22,23]. They aim to prove whether the use of bike-sharing is determined by transportation infrastructure [24], number of branches [19], length and density of bike lanes [22,25], social spectrum [26], and so on.

Bike–subway connection has been successfully used in urban transport to consider spatial accessibility aspects, i.e., design of travel chain [27,28]. These research projects typically start with the exploration of the influencing factors for connecting behavior from the perspective of subjective feelings [29]. Bike–metro–transit users pay more attention to bike parking safety, whereas bike–metro–walk users attach importance to parking spaces around metro stations [30]. Other studies by Yang et al. [31] show that key factors in connecting travel choices are gender, employment status, and comfort level associated with the travel experience. Metro–bike rides, for example, are more attractive to male drivers with lower grades or unpleasant commutes. Additionally, other determinants also play an important role in the connection between cycling and rail transit, including travel distance, age, income, personal attitude, travel purpose, and so on [32].

2.2. Traffic Bottleneck Modeling

Because of the increase in vehicle population and its environmental and socioeconomic consequences, such as parking difficulty, soaring urban congestion, and contribution to air and noise pollution, there has been a significant tendency in the past several years to shift traffic planning and management towards more problem-oriented models for traffic bottlenecks [33]. Although the definition of a traffic bottleneck remains uncertain, a traffic bottleneck generally refers to road sections or facilities with limited traffic capacity to objective factors [34]. The traffic capacity of bottleneck sections, which mainly exist in bends, ramps, intersections, and so on, is obviously lower than that of other locations. As a result, an algorithm addressing traffic bottleneck identification (TBI) is considered as the future solution to improve traffic flow and alleviate traffic congestion [35]. Many management and control technology developers have been advancing network models to improve identification accuracy and to promote the efficiency that is determined in terms of other traffic parameters such as delays, capacities, and so on [36–38]. It should be noted that traffic bottleneck identification subject to network has been mainly focused on microscopic traffic problems [39,40], instead of involving the regional scope from the spatial perspective. However, for bike-sharing with a high degree of spatial-temporal freedom, these models provide a good theoretical foundation for identifying and even explaining the mechanism of travel bottlenecks.

Several research projects model the influencing factors on traffic bottlenecks to understand the mechanism of traffic congestion [41]. Some of these studies focused on the traffic-flow-based modelling of different types of information, such as driver–vehicle–road and environmental factors and their impact on the transportation system [42,43]. The change in traffic infrastructures is identified as one of the key factors determining the efficiency of a traffic network and the role of management measures for them is analyzed [44,45]. Generally speaking, regional economic development and construction conditions are limited, resulting in imperfect infrastructure, limited road capacity, and low traffic efficiency [46]. At the same time, unreasonable planning and design of the transportation network as well as the poor built environment lead to low utilization efficiency of transportation infrastructure. A great deal of existing factors and models are particularly valuable to capture causes for bottlenecks of bike-sharing travel in this paper.

3. Method

3.1. Establishing Analysis Areas

In this section, we attempt to establish an analysis of areas of bottlenecks based on the hotspot detection of bike-sharing travel [47–50]. In recent years, kernel density estimation has been widely used in geospatial analysis and it is highly suitable for density estimation of large-scale spatial point data [51]. Figure 1 shows the principle of kernel density estimation. In the study area R , the kernel density estimation model takes any point as the center (i.e., kernel k) and calculates the density value of target points in bandwidth r , which is determined by the number and distance of material points in the bandwidth.

Figure 2 exhibits the algorithm flow of hotspot detection according to density field. Firstly, data preprocessing is carried out, such as eliminating abnormal data, filling up missing data, and extracting origin–destination from the bike-sharing trajectory. Then, “window analysis”, “minus”, “reclassifying”, “raster to polygon”, and so on is performed. Finally, the hotspots of bike-sharing travel are obtained. More importantly, we are able to establish the sensitive points of bike-sharing travel based on the “scanning heat value”.

The travel hotspots of bike-sharing are defined as analysis points, which are imported into a geographic database to establish the buffer areas around hotspots using geographic information system in order to establish the analysis areas, as shown the Figure 3.” (Sun C, Quan W. Evaluation of Bus Accessibility Based on Hotspot Detection and Matter-Element Analysis [J]. IEEE Access, 2020, PP(99):1-1).

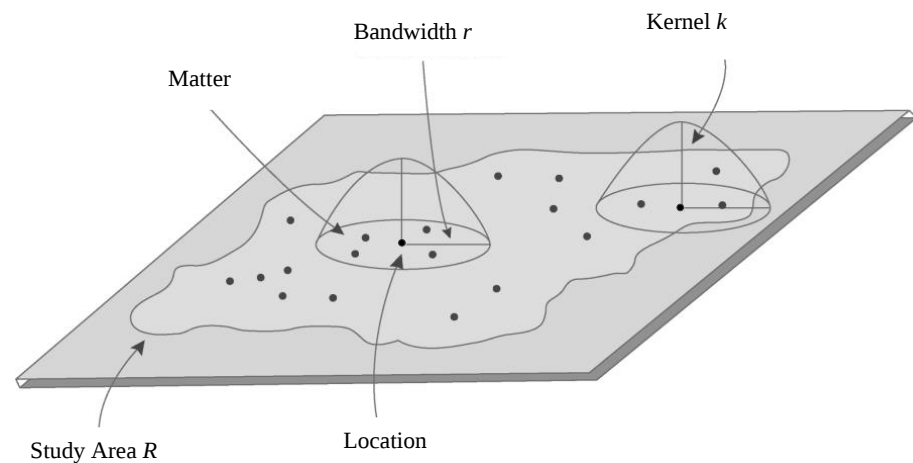


Figure 1. The model of kernel density estimation.

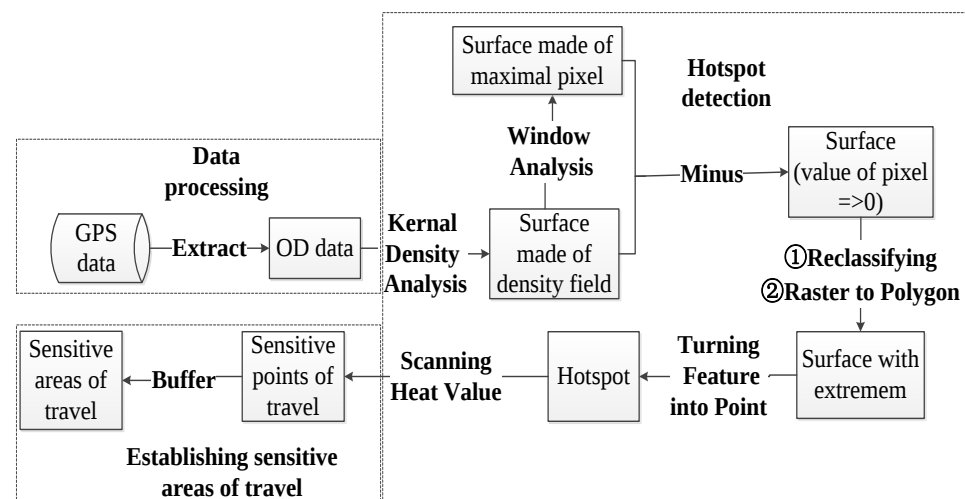


Figure 2. The flowchart of hotspot detection.

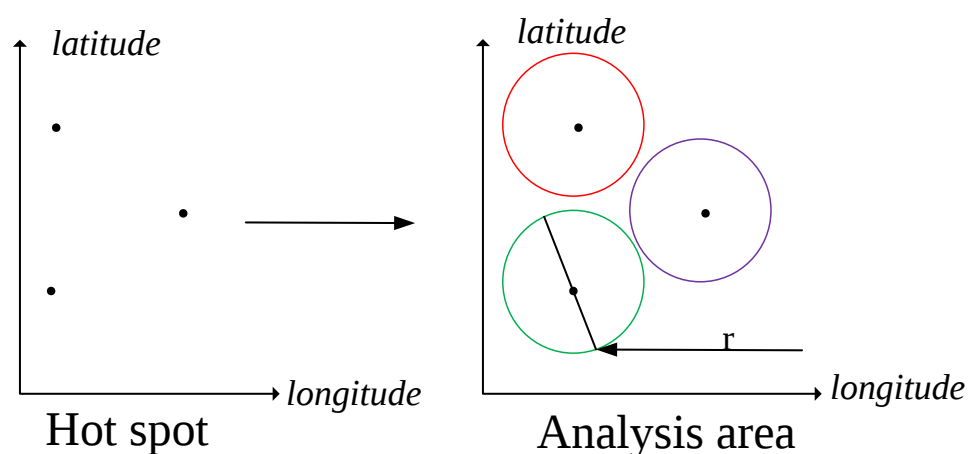


Figure 3. The analysis areas for modeling bottlenecks of bike-sharing travel. Black spots are hotspots (analysis spots); the circle is the 500 m buffer using the hotspot as the center point; r is the radius of 500 m.

3.2. Identifying Bike-Sharing Travel Bottlenecks

To identify the bottlenecks of bike-sharing travel, we introduce the residual analysis method and deploy trip generation of bike-sharing (TGB) to represent bike-sharing

demand. Herein, bike-sharing demand determined by endogenous factors is defined as endogenous demand, while bike-sharing demand determined by exogenous factors is defined as exogenous demand. Land use is one of the endogenous factors affecting TGB , while other environmental variables are the external factors. By modeling the relationships between land use and TGB , we can predict the ideal TGB determined by land use. The influence of other environmental factors on TGB can be represented by the change in the residual value, which is the difference between the observed TGB value and the predicted TGB value, as shown in Formula (1). This method effectively explores the respective effect of land use and other environmental factors on the TGB , so as to distinguish between endogenous and exogenous demand. In this paper, we define analysis areas with negative residual as the bottlenecks of bike-sharing travel, which can be deployed for investigating the internal driving factors. Briefly, because of the influence from other exogenous environmental factors, the ideal bike-sharing demand that should have been generated based on endogenous factors in these bottleneck areas tends to be weakened and even close to 0. The above definition is based on the following factors: every travel has a specific purpose and destination and travelers go from a specific point of interest to other points of interest according to their own purpose. In other words, the point of interest corresponding to land use is the source of travel occurrence and attraction, while other built environments, although they can affect the willingness and frequency of travel, are not the root cause of users' travel.

$$TGB_{HA} = TGB_{obs} - TGB_{CC} \quad (1)$$

TGB_{obs} is the actual observed value of the trip-generation of bike-sharing; TGB_{CC} is the predicted value of the trip-generation of bike-sharing; TGB_{HA} is the residual of the trip-generation of bike-sharing; and the analysis areas with a negative residual ($TGB_{HA} < 0$) are defined as bottlenecks of bike-sharing travel in this paper.

Generally, insufficient consideration of variables and autocorrelation are the difficulties in spatial statistical modeling. The former mainly refers to the unmeasurable difference in environmental stochasticity, which is described by residuals (TGB_{HA}) in this paper. However, there may also be spatial autocorrelation of TGB , which can lead to incorrect setting and biased results in the common regression model. In addition, as the travel demand cannot be less than zero, this paper introduces and improves the spatial-lag (SL) model and establishes Tobit-SL model based on Tobit regression. This model not only emphasizes the importance of the neighbor effect, but also accords better with the actual situation. Furthermore, as a feasible and simple method, it is reasonable to express land elements through geographical points of interest (POIs). In the Tobit-SL regression model, interest points are divided into several categories and used to represent different land use structures. The endogenous TGB induced by land use and neighbor effect is modeled as follows:

$$y_i = \rho \sum_{j=1}^n W_{ij} y_j + \sum_{q=1}^Q PI_{iq} \beta_q + C \quad (2)$$

$$TGB_{CC}(i) = \begin{cases} y & \text{if } y > 0 \\ 0 & \text{if } y \leq 0 \end{cases} \quad (3)$$

where $TGB_{CC}(i)$ is the trip-generation of bike-sharing influenced by endogenous factors (land use + the neighbor effect) in the i th analysis area; y_i is the result of spatial regression, a latent variable; W_{ij} is the (i, j) th element of the $n \times n$ order spatial weight matrix; Q is the number of kinds of interest points, which is 12 in this paper; PI_1 – PI_{12} are dining facilities, landscapes, public facilities, companies enterprises, educational facilities, financial insurance facilities, hotel facilities, living facilities, sports facilities, medical facilities, government departments, and residential facilities, respectively; and C is a constant term.

3.3. Investigating Bottlenecks' Causes

In this paper, bottlenecks of bike-sharing travel are represented by the analysis areas with negative residuals (TGB_{HA}). Therefore, based on the bottleneck identification results in Section 3.2, we model the fault tree of bike-sharing travel, in which the root cause of the travel bottleneck (top-tiered event) is found through step-by-step decomposition [52]. The logical relationship between events in each layer uses AND gate and OR gate to describe the structural function of fault tree of bike-sharing travel, following Formula (4).

$$\varphi(X) = \sum_{p=1}^{2^n} \varphi(X) \prod_{i=1}^n X_i^{Y_i} (1 - X_i)^{1-Y_i} \quad (4)$$

where p is the state combination serial number of the environmental factors (basic events); X_i is the i th environmental factor (basic event); Y_i is a state variable; and $\varphi(X)$ is the state value of travel bottleneck (top-tiered event) corresponding to the state combination of the p th event, which takes 1 or 0, respectively, indicating whether the bottleneck of bike-sharing occurs or does not occur. The structure of the fault tree model is shown in Figure 4 [53].

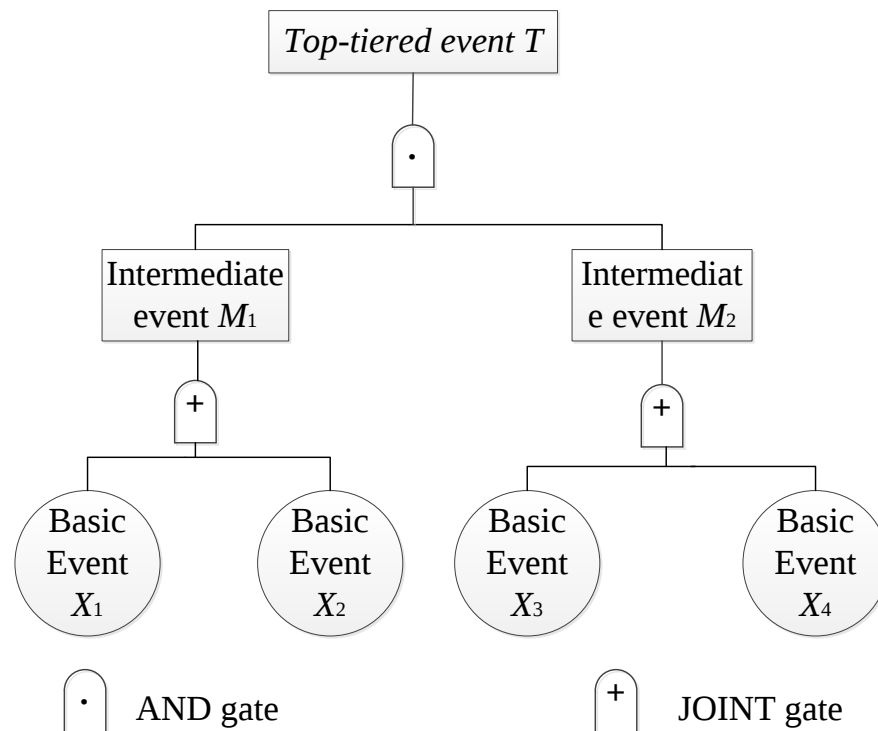


Figure 4. The demonstration of the structure of the fault tree model.

Bike-sharing service in an area should be regarded as a system. When TGB_{HA} is less than 0, it means that there are other unknown environmental variables that affect the service level of the system in the area, thus weakening the attraction of shared travel in the area. Therefore, by calculating the probability importance and critical importance of the fault tree, we can find out these basic factors that cause the bottleneck of the bike-sharing service system and then improve the sharing rate of bike-sharing travel in the transportation system. Among them, the probability importance degree is used to determine which basic event probability will rapidly reduce the occurrence probability of the top event. On the basis of probability importance, criticality further considers the sensitivity of basic events to top events, indicating the change rate of top event probability caused by the change rate of basic event probability [54]. See Formula (5) for the calculation method of probability and Formula (6) for the calculation method of critical importance.

$$I_{p(i)} = \frac{\partial P(T)}{\partial p_i} \quad (5)$$

$$C_i = \frac{\partial \ln P(T)}{\partial \ln p_i} = \frac{p_i}{P(T)} I_{p(i)} \quad (6)$$

where $I_{p(i)}$ is the probability importance of event i ; $P(T)$ is the probability of occurrence of a top event; p_i is the probability of the i th basic event; and C_i is the critical importance of event i .

The nodes in Bayesian network are divided into the following: ① evidence nodes, that is, variables with definite values; ② the target node, that is, the final inference target of a Bayesian network; and ③ intermediate nodes, that is, the connecting nodes between the evidence node and the target node. The modeling process of the Bayesian network based on a fault tree model is as follows [55,56].

Step 1. Determine nodes: The basic events, logic gates, and top events in the fault tree correspond to the evidence nodes, intermediate nodes, and target nodes in Bayesian networks, respectively.

Step 2. Establish a directed acyclic graph: The links between events in the fault tree correspond to the nodes in the Bayesian network, thus forming a directed acyclic graph.

Step 3. Generate the conditional probability table: The basic event probabilities and logic gates in the fault tree correspond to the prior probabilities of the evidence nodes in the Bayesian network and the conditional probability tables of the corresponding nodes, respectively.

Step 4. Calculate the posterior probability of the target node:

For the fault probability in this study, whether bottlenecks happen or not is set as $P(T = 1)$ and $P(T = 0)$, which are both fixed values. The joint probability distribution of each node in Bayesian network is as follows [57]:

$$P(T_1, T_2, \dots, T_n) = \prod_{i=1}^n P(T_i | \text{parents}(T_i)) \quad (7)$$

$$P(X = x_i, T = t_i) = P(T = t_i) \times P(X = x_i | T = t_i) \quad (8)$$

Further, the Bayesian formula is shown as follows:

$$P(T = t_i | X = x_i) = \frac{P(T = t_i) \times P(X = x_i | T = t_i)}{\sum_{i=1}^n P(X = x_i) P(T = t_i | X = x_i)} \quad (9)$$

Assuming that the bottleneck causes x_i and T are independent of each other, Formula (9) can be simplified as follows:

$$P(T | X = x_i) = \frac{P(T) \times P(X = x_i | T)}{\prod_{i=1}^n P(x_i)} \quad (10)$$

In the Bayesian network based on the fault tree, the prior probability of each intermediate node is determined according to the basic event probability and logic gate in the fault tree. According to the logic gate of the fault tree, there are multiple diagnosis modes among each evidence node, so the prior probability of the intermediate node is defined as follows:

$$P(M_k) = \prod_{d_w \in T_l} P(d_m | T) \quad (11)$$

where

$$P(d_m | T) = \prod_{x_i=true} P(x_i) \prod_{x_j=false} (1 - P(x_j)) \quad (12)$$

where $P(M_k)$ is the prior probability of the intermediate node; d_m is the diagnosis mode of each evidence node when T occurs; and is the probability that d_m is true given T .

Using the Bayesian network based on fault tree for analysis, can achieve the following goals [58]: ① Diagnostic reasoning. The final variable is defined as failure and the root nodes are sorted by comparing the probability changes. ② Causal reasoning. The evidence node is defined as a fault and the basic node that has the greatest influence on the target node is discriminated. ③ Sensitivity analysis of intermediate nodes is carried out by variance reduction. Assuming that variable Y is the target node with a states and variable X is the root node with b states, when the input value of X changes, the variance reduction (VR) of Y is as shown in Formula (13).

$$VR = V(Y) - V(Y | X) \quad (13)$$

where

$$V(Y) = \sum_a p(a) [N_a - E(Y)]^2 \quad (14)$$

$$V(Y | X) = \sum_a p(a | b) [N_a - E(Y | b)]^2 \quad (15)$$

$$E(Y) = \sum_a p(a) \quad (16)$$

where N_a is the value of state a ; $E(Y)$ is the initial posterior probability of variable Y ; $E(Y | b)$ is the expected value of variable Y after the evidence of variable X has been satisfied; $V(Y)$ is the initial square of variable Y ; and $V(Y | X)$ is the variance of variable Y after the evidence of variable X has been satisfied. The larger the VR value, the greater and more sensitive the influence of this variable on the target node.

4. Case Study

4.1. Study Area

This paper uses Beijing as a case study city. Bike-sharing travel is popular in the city of Beijing. This is because Beijing has invested a lot of money into bike-sharing in recent years, with a high coverage rate and utilization rate, among the highest in China. Therefore, by means of bottleneck fault tree–Bayesian networks, this paper aims to investigate the internal mechanisms of bottlenecks in bike-sharing travel for Beijing city. The findings presented here can contribute to adjusting the urban structure and reconstructing the green infrastructure layout. The location and urban morphology of Beijing city is shown in Figure 5.

4.2. Data Description

This paper takes Beijing bike-sharing data provided by open data sources as research data (<https://www.biendata.xyz/competition/mobike/data/>, accessed on 30 August 2022). The main fields of the dataset include orderID, bikeID, and so on. After data preprocessing (including the deletion of invalid data, redundant, and abnormal data), they are imported into ArcGIS software. Using the clip tool, the OD data of the bike-sharing travel within the study area are obtained. In order to determine the amount of TGB induced by land elements, all POI data in Beijing are obtained using crawler tools, which are divided into 12 categories, mainly including catering facilities, landscapes, and so on, as stated in Formula (2). At the same time, the data of the urban road network, bus stations, subway stations, and intersections are crawled. Secondly, the street view data of the Baidu map are used to obtain the green area, sidewalk length, and bicycle lane length of the road. Finally,

the spatial distribution of topography, altitude, air quality, and precipitation in Beijing was obtained using the literature method.



Figure 5. The location of the research zone.

5. Results and Discussion

5.1. Bottleneck Identification Demonstration

Based on the kernel density analysis algorithm, the OD data are employed to obtain the density field of bike-sharing travel in Beijing. Then, according to the model in Section 3.1, the hotspots' detection flow in ArcGIS is used to calculate all travel hotspots of bike-sharing. Subsequently, with all of the travel hotspots (analysis points) of bike-sharing as the center, analysis zones are built as the buffer zone with a search radius of 500 m and exported into the geographical database, as shown in Figure 6.

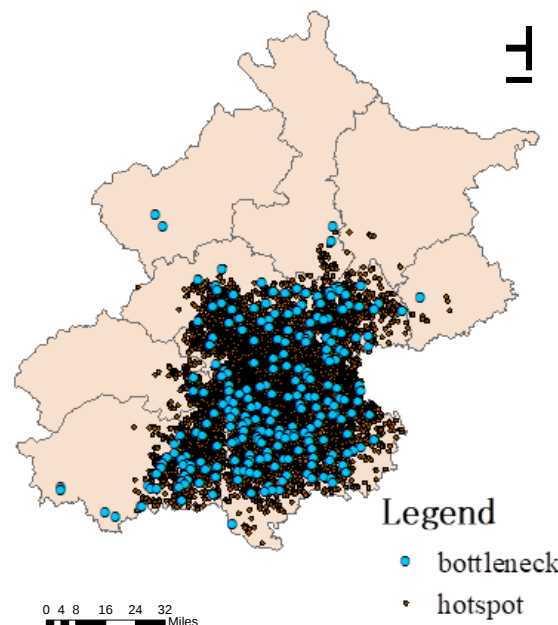


Figure 6. The top 155 analysis regions with the largest residuals.

In order to ensure the accuracy of identification, we first employ Moran's I index [59,60] and semi-variograms [61,62] to test the spatial correlation and heterogeneity of bike-sharing demand. The results show the following: global Moran's $I = 0.406954$, standardized statistic $Z = 535.810289$, significance level $P_1 = 0$, and confidence coefficient $CC = 99\%$. Furthermore, the range of semi-variogram is 1860 m, which is shown as Figure S1 in supplementary files.

Next, the heat values, namely, the density field values in the analysis area, are taken as the representation of the *TGB* and set as the dependent variable. The number of POIs in the analysis area is used as an independent variable to fit Formulas (2) and (3), as follows. The results show the following: overall significance $p < 0.01$ as well as with $R^2 = 0.678$, which means that the original hypothesis is rejected, that is, the explanatory variables used this model are valid, and the establishment of bike-sharing travel demand model is of great significance. The final results are shown as Table S1 in supplementary files.” (Sun C, Lu J. Bike-sharing Trips Spatial Heterogeneity and Driving Factors. *Journal of Transportation Systems Engineering and Information Technology*, 2022, 22(03): 198–206).

This Tobit-SL model is employed to predict the theoretical *TGB* in all analysis areas, which presents the demand induced by land-use and the neighbor effect. The influence of other environmental factors on *TGB* is described by the change in the residual values according to Formula (1), and the analysis areas with residual values less than 0 are defined as travel bottlenecks of bike-sharing. In order to reduce difficulty caused by too much data, the residuals are divided into several intervals based on the Jenk’s natural breaks method [63,64], and the top 155 analysis regions with the largest residuals are extracted for Bayesian network modeling, as shown in Figure 6.

5.2. Demonstration of the Fault Tree–Bayesian Network

When drawing the fault tree of bike-sharing travel, the top event is the bottlenecks, followed by the natural geographical elements, the built environment of the traffic area, and the socio-economic elements. Most influencing factors such as the number of bus stops, length of bus lines, and so on are continuous variables, which cannot be dealt with by Bayesian networks. Therefore, in order to transform the original data format into an appropriate modeling format, it is necessary to discretize the data. The discretizing algorithm used herein is a non-hierarchical clustering algorithm based on distance, which is also called K-means. Its main principle is to divide the data into predetermined classes based on a minimum error function and use distance as a similarity evaluation standard. This simply means that, the closer the distance between two objects, the greater their similarity. By clustering and discretizing all of the environmental elements in the analysis areas, all of the influencing factors are divided into five grades. The most unfavorable level for bike-sharing travel is set as the basic event of this model, such as poor air (worst), heavy rain (worst), serious traffic congestion (worst), and so on. Therefore, the fault tree model for bottlenecks of bike-sharing travel is as shown in Figure 7.

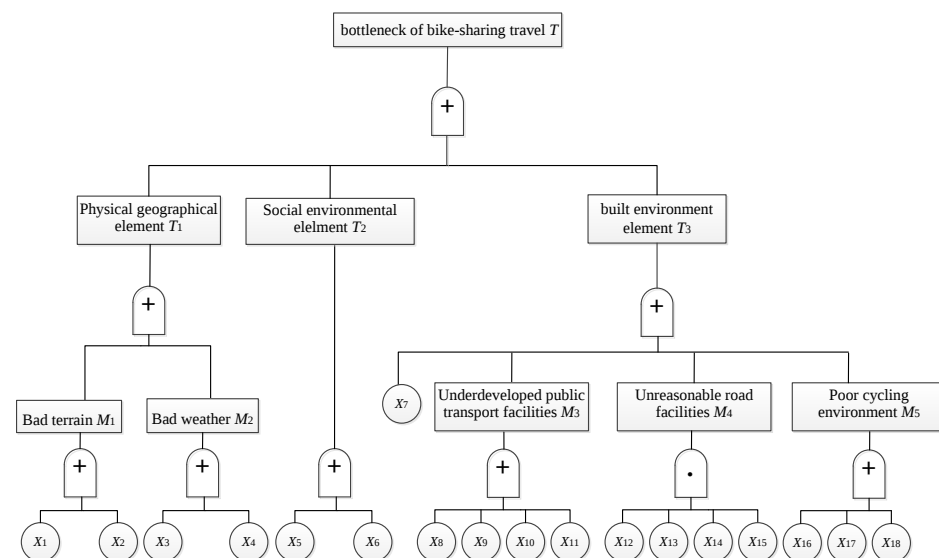


Figure 7. The fault tree model for bottlenecks of bike-sharing travel.

- | | | |
|--------------------------------------|---------------------------------|------------------------------------|
| X_1 : High altitude | X_2 : Heavily heaved terrain | X_3 : Heavy rain |
| X_4 : Poor air | X_5 : High income | X_6 : Serious traffic congestion |
| X_7 : Serious Home-Work separation | X_8 : Few bus stops | X_9 : Few bus lines |
| X_{10} : Small density of bus lane | X_{11} : Few subway station | X_{12} : Low road density |
| X_{13} : Few branch roads | X_{14} : Few car parking | X_{15} : Low sidewalk density |
| X_{16} : Low density of bike lanes | X_{17} : Low green area ratio | X_{18} : Excessive intersections |

The Bayesian network is mainly composed of nodes and conditional probability tables, which are mapped to each event and logic gate of the fault tree. Figure 8 shows the conditional probability table of OR gate and AND gate (taking T_1 node as an example). The Bayesian network is determined by the topology and model parameters and its topology is shown in Figure 8. The model parameters refer to the prior probability of each evidence node and the conditional probability of the intermediate node and the target node. Among them, the prior probability of the evidence node is determined by the basic event probability of the fault tree. The conditional probability tables of the intermediate node and the target node are determined by independent probability input. The final Bayesian network model of bottlenecks of bike-sharing travel is shown in Figure 9.

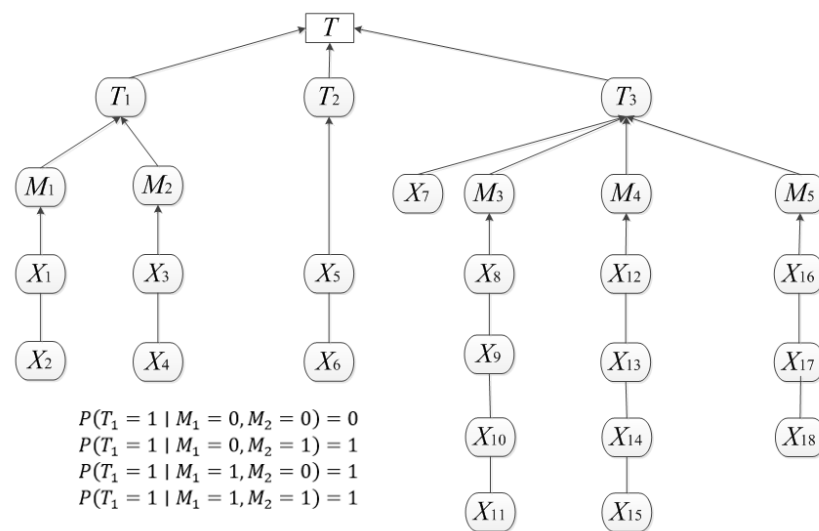


Figure 8. Topological structure of the Bayesian network of bottlenecks of bike-sharing travel.

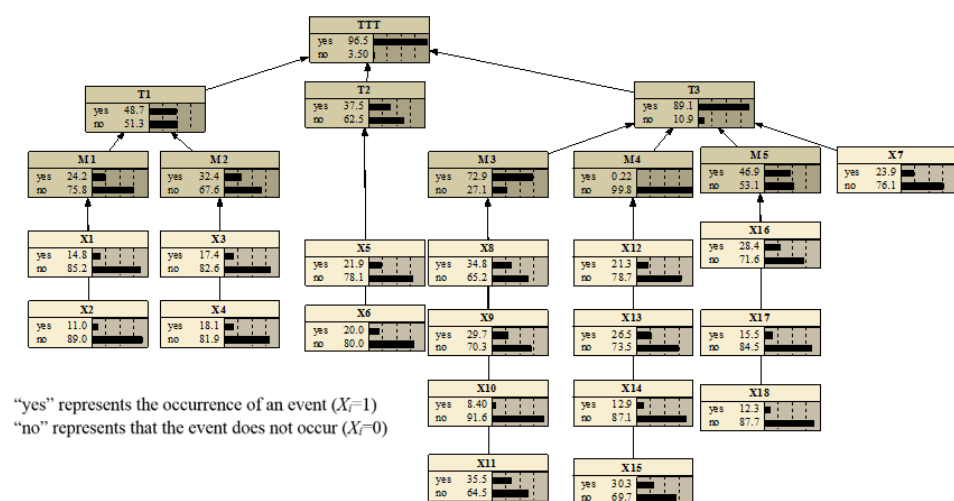


Figure 9. The Bayesian network of bottlenecks of bike-sharing travel based on a fault tree (for example, the probability of the occurrence of event X_7 is 23.9% and the probability of non-occurrence is 76.1%).

5.3. Interpretation of Bottleneck Causes

(1) Quantitative Evaluation of Fault Tree

According to Formula (4), the structural function of the fault tree is as follows:

$$\varphi(X) = X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8 + X_9 + X_{10} + X_{11} + X_{12}X_{13}X_{14}X_{15} + X_{16} + X_{17} + X_{18} \quad (17)$$

Using Formula (5), the probability importance of basic events is calculated as shown in Table 1.

Table 1. The probability importance of basic events.

Event ID	$I_{p(i)}$	Event ID	$I_{p(i)}$	Event ID	$I_{p(i)}$	Event ID	$I_{p(i)}$	Event ID	$I_{p(i)}$
X_1	1	X_5	1	X_9	1	X_{13}	0.0083	X_{17}	1
X_2	1	X_6	1	X_{10}	1	X_{14}	0.0171	X_{18}	1
X_3	1	X_7	1	X_{11}	1	X_{15}	0.0073		
X_4	1	X_8	1	X_{12}	0.0104	X_{16}	1		

Combined with the probability importance results, the critical importance order of basic events calculated according to Formula (6) is as follows:

$$C_{11} > C_8 > C_9 > C_{16} > C_7 > C_5 > C_6 > C_4 > C_3 > C_{17} > C_1 > C_{18} > C_2 > C_{10} > C_{12} > C_{15} > C_{14} > C_{13} \quad (18)$$

From the above inequality, we can know the influencing degree of each basic event on the travel bottleneck in bike-sharing. Among them, the few subway stations, few bicycle lanes, serious separation of occupation and residence, too many intersections, and few branch roads are the main causes for bottlenecks of bike-sharing travel. When the probabilities of these five events change, the probability of the top event changes greatly, that is, if the probabilities of these five events can be effectively reduced, the probability of bike-sharing travel bottlenecks in the city can be reduced to the greatest extent or the sharing rate of bike travel can be increased, which is ultimately conducive to alleviating traffic congestion and reducing urban pollution.

(2) Quantitative Evaluation of the Fault Tree-Based Bayesian Network

For quantitative analysis of the Bayesian network based on the fault tree, the maximum posterior probability of each intermediate node T_1 , T_2 , and T_3 is calculated according to Formula (10). For example, for T_1 , its maximum posterior probability is shown as follows:

$$P(T_1|M_1, M_2) = \frac{P(T_1)P(M_1, M_2|T_1)}{P(M_1)P(M_2)} \quad (19)$$

Among them, for nodes M_1 and M_2 , it is necessary to judge the diagnosis mode according to the underlying evidence nodes. For example, for node M_1 , its lower evidence nodes (X_1 , X_2) determine its diagnosis mode as follows:

$$d_1 : (x_1, \overline{x_2}); d_1 : (x_2, \overline{x_1}); d_1 : (x_1, x_2) \quad (20)$$

According to Formula (11), the maximum posterior probabilities of intermediate nodes T_1 , T_2 , and T_3 are 0.650, 0.614, and 0.998, respectively, that is, the contribution rates of natural environment, social environment, and built environment to the occurrence of travel bottleneck in bike-sharing are 48.7%, 37.5%, and 89.1%, respectively. The total contribution percentage is greater than 100%, which shows that the bottleneck is caused by various factors. In addition, there are dynamic and complex interactions between various factors. The built environment accounts for the largest proportion, which may be caused by users being more sensitive to changes in transportation infrastructure and other factors, as well

as the high correlation between bike-sharing and other modes of travel. For the natural environment, “poor air quality” is the most important reason for the travel bottleneck in bike-sharing, so special attention should be paid to such factors when configuring and dispatching bike-sharing within one region. Finally, the social and economic factors account for a certain proportion. The reason is that, for high-income groups, the time cost is more important, and bike-sharing obviously does not meet the demand. In addition, in areas with severe traffic congestion, the riding environment will be even worse, which will affect the assessment of riding safety.

On the premise that the travel bottleneck occurs in bike-sharing, the occurrence probability of the target node is defined as “1”. Using Bayesian network diagnosis reasoning, the factors that have a great influence on the travel bottleneck are diagnosed by comparing the probability changes of the evidence nodes. The diagnosis reasoning results are shown in Table 2.

Table 2. The diagnosis reasoning results.

	Basic Elements								
	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉
Prior probability	14.8	11.0	17.4	18.1	21.9	20.0	23.9	34.8	29.7
Inferred probability	15.3	11.4	18.0	18.8	22.7	20.7	24.8	36.1	30.8
Importance order	14	17	12	11	8	10	7	2	3
Basic elements	X ₁₀	X ₁₁	X ₁₂	X ₁₃	X ₁₄	X ₁₅	X ₁₆	X ₁₇	X ₁₈
Prior probability	8.7	36.8	21.3	26.5	12.9	30.3	28.4	15.5	12.3
Inferred probability	8.77	37.0	21.3	26.5	12.9	30.3	29.4	16.1	12.7
Importance order	18	1	9	6	15	4	5	13	16

It can be seen from Table 2 that the order of importance of the basic influencing factors of travel bottlenecks in each bike-sharing is as follows:

$$\begin{aligned}
 &X_{11} > X_8 > X_9 > X_{15} > X_{16} > X_{13} > X_7 > X_5 > X_{12} > \\
 &X_6 > X_4 > X_3 > X_{17} > X_1 > X_{14} > X_{18} > X_2 > X_{10}
 \end{aligned}
 \quad (21)$$

Further, the sensitivity of the whole network is analyzed. Using Formula (14), with the help of Netica simulation software, we calculate the variance reduction of each evidence node in the Bayesian network of bike-sharing travel bottleneck with T as the target node. Among them, a is “ $X_i = 1$ or 0 ($i = 1, 2, \dots, n$)” and “ b is $T = 1$ or 0 ”. Therefore, its calculation expression is simplified following Formula (22). In addition, the results of the sensitivity analysis are presented in Table 3.

$$VR_{x_i} = \sum_a p(a)[N_a - \sum_a p(a)N_a]^2 - \sum_a p(a|b)[N_a - E(x_i - b)] \quad (22)$$

According to Table 3, it is found that the most sensitive evidence nodes (basic factors) in the Bayesian network are few subway stations, few bus stops, few bus lines, a low density of bicycle lanes, and serious home–work separation. Therefore, when making bike-sharing dispatching strategies or planning MaaS and slow-moving traffic systems, we should focus more on the above influencing factors of bike-sharing travel bottlenecks, so as to match supply and demand and enhance the attraction of shared travel. Combined with the characteristics of urban bike-sharing travel in previous studies, it can be seen that this conclusion accords with the actual situation [22,25]. More importantly, a comprehensive and detailed analysis of natural environmental factors, social environmental factors, and built environmental factors will help to adjust the urban structure and reconstruct the infrastructure layout. This means that we can eliminate the bottleneck from the perspective of external factors, so as to enhance the generation of bike-sharing trips in the whole spatial area and to make the greatest contribution to developing green transport and alleviating

traffic congestion. In addition, by comparing and analyzing the diagnostic reasoning results of the bike-sharing travel bottleneck Bayesian network for the quantitative analysis results of the fault tree, we conclude that the output results of the two models are roughly the same. However, the calculation process of the bike-sharing travel bottleneck Bayesian network based on the fault tree is simpler and faster, and the most important thing is that all of the information of environmental factors can be used for parallel computation. Moreover, based on conditional probability, the model analyzes the importance of various basic environmental factors according to variance reduction. In fact, it realizes a polymorphic logic and can be extended to research into other traffic bottlenecks.

Table 3. The results of the sensitivity analysis.

Basic Elements							
	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Mutual info	0.00824	0.00599	0.00983	0.01027	0.01272	0.01148	0.01406
Percent	3.77	2.74	4.5	4.7	5.82	5.25	6.43
$VR_{Xi}(10^{-2})$	0.02124	0.01511	0.02576	0.02703	0.03429	0.03057	0.03841
Basic elements	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}
Mutual info	0.02206	0.01816	0.00451	0.02262	0.00000	0.00000	0.00000
Percent	10.1	8.3	2.06	10.3	0.000216	0.000162	0.000388
$VR_{Xi}(10^{-2})$	0.06527	0.05166	0.01121	0.06730	0.00000	0.00000	0.00000
Basic elements	X_{15}	X_{16}	X_{17}	X_{18}			
Mutual info	0.00000	0.01721	0.00866	0.00675			
Percent	9.52×10^{-5}	7.87	3.96	3.09			
$VR_{Xi}(10^{-2})$	0.00000	0.04850	0.02243	0.01715			

6. Conclusions

We focus on the problem of modeling bottlenecks of bike-sharing travel in hotspot areas with generalized spatial autocorrelation between demands. An SL-Tobit analysis model is proposed, which can be adjusted to distinguish between endogenous and exogenous needs and to consider neighborhood effects. Furthermore, a solution method based on the “Bayesian network based on a fault tree” is suitable for capturing the bottleneck sensitivity of different environmental factors.

Although the causes are more complicated, the sensitivity assessment of bottleneck mechanisms showed some interesting conclusions. We modeled the fault tree of bike-sharing travel, in which the root causes (environmental factors) of bottlenecks (top-tiered event) were found through step-by-step decomposition. By focusing on accuracy improvement, the fault tree Bayesian network overcomes the influence of the lack of variables. Furthermore, a reliable variance-reduction consequence of 155 analysis areas with the largest residual is that the bottlenecks of bike-sharing travel tended to be formulated by few subway station, few bus stops, few bus lines, a low density of bike lanes, and serious home-work separation, which play a relatively decisive role in weakening endogenous demand from land use. Even more interesting, it seems that the introduction of this mechanism assessment increased application value to the project: ① matched supply and demand and enhanced the attraction of shared travel; ② adjusted the urban structure and reconstructed the infrastructure layout; and ③ enhanced TGB and alleviated traffic congestion.

We put forward a few questions that need to be discussed in future work. We need additional reasoning tests to understand the propagation and dissipation process of bottlenecks of bike-sharing travel. There is certain motivation for demonstrating how the influence of time-series indexes may change the distribution and importance of bottlenecks by considering urban roads with a complex network. Lastly, for the purpose of being applied to optimize the efficiency of connections with other public transport, the mechanism

assessment presented here may need to incorporate a spatial accessibility approach for the direct estimation of spatial-time obstruction.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/ijgi11110551/s1>.

Author Contributions: Sun Chao: Conceptualization, methodology, formal analysis, writing—original draft preparation; Lu Jian: writing—review and editing, supervision, funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China under Grant 52072071 and the Postgraduate Research and Practice Innovation Program of Jiangsu Province (No. KYCX22_0285).

Data Availability Statement: The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Cho, S.H.; Shin, D. Estimation of Route Choice Behaviors of Bike-Sharing Users as First- and Last-mile Trips for Introduction of Mobility-as-a-Service (MaaS). *KSCE J. Civ. Eng.* **2022**, *26*, 3102–3113. [\[CrossRef\]](#)
2. Hofmann, C.; Staehr, T.; Cohen, S.; Stricker, N.; Haefner, B.; Lanza, G. Augmented Go & See: An approach for improved bottleneck identification in production lines. *Procedia Manuf.* **2019**, *31*, 148–154. [\[CrossRef\]](#)
3. Hale, D.; Chrysikopoulos, G.; Kondyli, A.; Ghiasi, A. Evaluation of data-driven performance measures for comparing and ranking traffic bottlenecks. *IET Intell. Transp. Syst.* **2021**, *15*, 504–513. [\[CrossRef\]](#)
4. Wang, X.; Cheng, Z.; Trépanier, M.; Sun, L. Modeling bike-sharing demand using a regression model with spatially varying coefficients. *J. Transp. Geogr.* **2021**, *93*, 103059. [\[CrossRef\]](#)
5. Gebhart, K.; Noland, R.B. The impact of weather conditions on bikeshare trips in Washington, DC. *Transportation* **2014**, *41*, 1205–1225. [\[CrossRef\]](#)
6. Kim, M.; Cho, G.-H. Analysis on bike-share ridership for origin-destination pairs: Effects of public transit route characteristics and land-use patterns. *J. Transp. Geogr.* **2021**, *93*, 103047. [\[CrossRef\]](#)
7. Du, Y.; Deng, F.; Liao, F. A model framework for discovering the spatio-temporal usage patterns of public free-floating bike-sharing system. *Transp. Res.* **2019**, *103*, 39–55. [\[CrossRef\]](#)
8. Zk, A.; Hua, C. Understanding bike sharing travel patterns: An analysis of trip data from eight cities. *Phys. A Stat. Mech. Its Appl.* **2019**, *515*, 785–797.
9. Zi, W.; Xiong, W.; Chen, H.; Chen, L. TAGCN: Station-level demand prediction for bike-sharing system via a temporal attention graph convolution network. *Inf. Sci.* **2021**, *561*, 274–285. [\[CrossRef\]](#)
10. Yu, S.; Liu, G.; Yin, C. Understanding spatial-temporal travel demand of free-floating bike sharing connecting with metro stations. *Sustain. Cities Soc.* **2021**, *74*, 103162. [\[CrossRef\]](#)
11. Ma, X.; Ji, Y.; Yuan, Y.; Van Oort, N.; Jin, Y.; Hoogendoorn, S. A comparison in travel patterns and determinants of user demand between docked and dockless bike-sharing systems using multi-sourced data. *Transp. Res. Part A Policy Pract.* **2020**, *139*, 148–173. [\[CrossRef\]](#)
12. Wei, Z.; Zhen, F.; Mo, H.; Wei, S.; Peng, D.; Zhang, Y. Travel Behaviours of Sharing Bicycles in the Central Urban Area Based on Geographically Weighted Regression: The Case of Guangzhou, China. *Chin. Geogr. Sci.* **2021**, *31*, 54–69. [\[CrossRef\]](#)
13. Soltani, A.; Mátrai, T.; Camporeale, R.; Allan, A. Exploring Shared-Bike Travel Patterns Using Big Data: Evidence in Chicago and Budapest. In *Computational Urban Planning and Management for Smart Cities*; Springer: Cham, Switzerland, 2019. [\[CrossRef\]](#)
14. El-Assi, W.; Mahmoud, M.S.; Habib, K.N. Effects of built environment and weather on bike sharing demand: A station level analysis of commercial bike sharing in Toronto. *Transportation* **2017**, *44*, 589–613. [\[CrossRef\]](#)
15. Kim, K. Investigation on the effects of weather and calendar events on bike-sharing according to the trip patterns of bike rentals of stations. *J. Transp. Geogr.* **2018**, *66*, 309–320. [\[CrossRef\]](#)
16. Lin, P.; Weng, J.; Liang, Q.; Alivanistos, D.; Ma, S. Impact of Weather Conditions and Built Environment on Public Bikesharing Trips in Beijing. *Netw. Spat. Econ.* **2020**, *20*, 1–17. [\[CrossRef\]](#)
17. Cao, Z.; Gao, F.; Li, S.; Wu, Z.; Guan, W.; Ho, H.C. Ridership exceedance exposure risk: Novel indicators to assess PM2.5 health exposure of bike sharing riders. *Environ. Res.* **2021**, *197*, 111020. [\[CrossRef\]](#)
18. Zhao, J.; Fan, W.; Zhai, X. Identification of land-use characteristics using bicycle sharing data: A deep learning approach. *J. Transp. Geogr.* **2020**, *82*, 102562. [\[CrossRef\]](#)
19. Faghih-Imani, A.; Eluru, N.; El-Geneidy, A.M.; Rabbat, M.; Haq, U. How land-use and urban form impact bicycle flows: Evidence from the bicycle-sharing system (BIXI) in Montreal. *J. Transp. Geogr.* **2014**, *41*, 306–314. [\[CrossRef\]](#)

20. Osama, A.; Sayed, T.; Bigazzi, A.Y. Models for estimating zone-level bike kilometers traveled using bike network, land use, and road facility variables. *Transp. Res. Part A Policy Pract.* **2017**, *96*, 14–28. [\[CrossRef\]](#)
21. Osama, A.; Sayed, T. Evaluating the impact of bike network indicators on cyclist safety using macro-level collision prediction models—ScienceDirect. *Accid. Anal. Prev.* **2016**, *97*, 28–37. [\[CrossRef\]](#)
22. Mateo-Babiano, I.; Bean, R.; Corcoran, J.; Pojani, D. How does our natural and built environment affect the use of bicycle sharing? *Trans. Res. Part A Policy Pract.* **2016**, *94*, 295–307. [\[CrossRef\]](#)
23. Yeran, S.; Amin, M.; Xuke, H.; Weikai, W. Investigating Impacts of Environmental Factors on the Cycling Behavior of Bi-cycle-Sharing Users. *Sustainability* **2017**, *9*, 1060.
24. Yang, R.; Long, R. Analysis of the Influencing Factors of the Public Willingness to Participate in Public Bicycle Projects and Intervention Strategies—A Case Study of Jiangsu Province, China. *Sustainability* **2016**, *8*, 349. [\[CrossRef\]](#)
25. Zhang, Y.; Thomas, T.; Brussel, M.; van Maarseveen, M. Exploring the impact of built environment factors on the use of public bikes at bike stations: Case study in Zhongshan, China. *J. Transp. Geogr.* **2017**, *58*, 59–70. [\[CrossRef\]](#)
26. Campbell, A.A.; Cherry, C.R.; Ryerson, M.S.; Yang, X. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. *Trans. Res. Part C Emerg. Technol.* **2016**, *67*, 399–414. [\[CrossRef\]](#)
27. Ma, X.; Ji, Y.; Yang, M.; Jin, Y.; Tan, X. Understanding bikeshare mode as a feeder to metro by isolating metro-bikeshare transfers from smart card data. *Transp. Policy* **2018**, *71*, 57–69. [\[CrossRef\]](#)
28. Chen, C.-F.; Cheng, W.-C. Sustainability SI: Exploring Heterogeneity in Cycle Tourists' Preferences for an Integrated Bike-Rail Transport Service. *Netw. Spat. Econ.* **2016**, *16*, 83–97. [\[CrossRef\]](#)
29. Ji, Y.; Fan, Y.; Ermagun, A.; Cao, X.; Wang, W.; Das, K. Public bicycle as a feeder mode to rail transit in China: The role of gender, age, income, trip purpose, and bicycle theft experience. *Int. J. Sustain. Transp.* **2017**, *11*, 308–317. [\[CrossRef\]](#)
30. Yang, M.; Zhao, J.; Wang, W.; Liu, Z.; Li, Z. Metro commuters' satisfaction in multi-type access and egress transferring groups. *Transp. Res. Part D Transp. Environ.* **2015**, *34*, 179–194. [\[CrossRef\]](#)
31. Yang, M.; Liu, X.; Wang, W.; Li, Z.; Zhao, J. Empirical Analysis of a Mode Shift to Using Public Bicycles to Access the Suburban Metro: Survey of Nanjing, China. *J. Urban Plan. Dev.* **2016**, *142*, 05015011. [\[CrossRef\]](#)
32. Zhao, P.; Li, S. Bicycle-metro integration in a growing city: The determinants of cycling as a transfer mode in metro station areas in Beijing. *Transp. Res. Part A Policy Pract.* **2017**, *99*, 46–60. [\[CrossRef\]](#)
33. Zhuang, Y.; Liu, Z.; Schadschneider, A.; Yang, L.; Huang, J. Exploring the behavior of self-organized queuing for pedestrian flow through a non-service bottleneck. *Phys. A Stat. Mech. Its Appl.* **2021**, *562*, 125186. [\[CrossRef\]](#)
34. Qu, Q.-K.; Chen, F.-J.; Zhou, X.-J. Road traffic bottleneck analysis for expressway for safety under disaster events using blockchain machine learning. *Saf. Sci.* **2019**, *118*, 925–932. [\[CrossRef\]](#)
35. Li, C.; Yue, W.; Mao, G.; Xu, Z. Congestion Propagation Based Bottleneck Identification in Urban Road Networks. *IEEE Trans. Veh. Technol.* **2020**, *69*, 4827–4841. [\[CrossRef\]](#)
36. Chiou, S.-W. *An Efficient Bundle-Like Algorithm for Data-Driven Multi-objective Bi-Level Signal Design for Traffic Networks with Hazardous Material Transportation BT—Data Science and Digital Business*; Márquez, F.P.G., Lev, B., Eds.; Springer International Publishing: Cham, Switzerland, 2019; pp. 191–220.
37. Zhang, Y.; Zhou, Y.; Lu, H.; Fujita, H. Cooperative multi-agent actor-critic control of traffic network flow based on edge computing. *Futur. Gener. Comput. Syst.* **2021**, *123*, 128–141. [\[CrossRef\]](#)
38. Nagatani, T. Traffic flow stabilized by matching speed on network with a bottleneck. *Phys. A Stat. Mech. Its Appl.* **2020**, *538*, 122838. [\[CrossRef\]](#)
39. Monache, M.L.D.; Goatin, P. A numerical scheme for moving bottlenecks in traffic flow. *Bull. Braz. Math. Soc. New Ser.* **2016**, *47*, 605–617. [\[CrossRef\]](#)
40. Qi, H.; Liu, M.; Wang, D.; Chen, M. Spatial-Temporal Congestion Identification Based on Time Series Similarity Considering Missing Data. *PLoS ONE* **2016**, *11*, e0162043. [\[CrossRef\]](#)
41. Dong, H.; Ma, S.; Guo, M.; Liu, D. Research on Analysis Method of Traffic Congestion Mechanism Based on Improved Cell Transmission Model. *Discret. Dyn. Nat. Soc.* **2012**, *2012*, 854654. [\[CrossRef\]](#)
42. Wang, W.-X.; Wang, B.-H.; Zheng, W.-C.; Yin, C.-Y.; Zhou, T. Advanced information feedback in intelligent traffic systems. *Phys. Rev. E* **2005**, *72*, 066702. [\[CrossRef\]](#)
43. Lee, K.; Hui, P.M.; Wang, B.-H.; Johnson, N.F. Effects of Announcing Global Information in a Two-Route Traffic Flow Model. *J. Phys. Soc. Jpn.* **2001**, *70*, 3507–3510. [\[CrossRef\]](#)
44. Li, X.; Zhang, J.; Li, Z.; Han, X. Influence of Different Management Measures on Traffic Bottleneck Induced by the Reduction of Lanes. *Inf. Technol. J.* **2012**, *11*, 388–391. [\[CrossRef\]](#)
45. D'Ariano, A.; Pacciarelli, D.; Pranzo, M. Assessment of flexible timetables in real-time traffic management of a railway bottleneck. *Transp. Res. Part C Emerg. Technol.* **2007**, *16*, 232–245. [\[CrossRef\]](#)
46. Yang, H.; Bell, M.; Meng, Q. Modeling the capacity and level of service of urban transportation networks. *Transp. Res. Part B Methodol.* **2000**, *34*, 255–275. [\[CrossRef\]](#)
47. Wilson, S.E.; Bunko, A.; Johnson, S.; Murray, J.; Wang, Y.; Deeks, S.L.; Crowcroft, N.S.; Friedman, L.; Loh, L.C.; MacLeod, M.; et al. The geographic distribution of un-immunized children in Ontario, Canada: Hotspot detection using Bayesian spatial analysis. *Vaccine* **2021**, *39*, 1349–1357. [\[CrossRef\]](#) [\[PubMed\]](#)

48. Zhang, Y.; Min, J.; Liu, C.; Li, Y. Hotspot Detection and Spatiotemporal Evolution of Catering Service Grade in Mountainous Cities from the Perspective of Geo-Information Tupu. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 287. [\[CrossRef\]](#)
49. Yu, W. Discovering Frequent Movement Paths From Taxi Trajectory Data Using Spatially Embedded Networks and Association Rules. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 855–866. [\[CrossRef\]](#)
50. Bandyopadhyaya, R.; Mitra, S. Fuzzy Cluster-Based Method of Hotspot Detection with Limited Information. *J. Transp. Saf. Secur.* **2014**, *7*, 307–323. [\[CrossRef\]](#)
51. Aitchison, J.; Lauder, I.J. Kernel Density Estimation for Compositional Data. *Appl. Stat.* **2018**, *34*, 129–137. [\[CrossRef\]](#)
52. de Oña, J.; Mujalli, R.O.; Calvo, F.J. Analysis of traffic accident injury severity on Spanish rural highways using Bayesian networks. *Accid. Anal. Prev.* **2010**, *43*, 402–411. [\[CrossRef\]](#)
53. Kumar, M.; Kaushik, M. System failure probability evaluation using fault tree analysis and expert opinions in intuitionistic fuzzy environment. *J. Loss Prev. Process Ind.* **2020**, *67*, 104236. [\[CrossRef\]](#)
54. Liu, P.; Yang, L.; Gao, Z.; Li, S.; Gao, Y. Fault tree analysis combined with quantitative analysis for high-speed railway accidents. *Saf. Sci.* **2015**, *79*, 344–357. [\[CrossRef\]](#)
55. Bobbio, A.; Portinale, L.; Minichino, M.; Ciancamerla, E. Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. *Reliab. Eng. Syst. Saf.* **2001**, *71*, 249–260. [\[CrossRef\]](#)
56. Duan, R.-X.; Zhou, H.-L. A New Fault Diagnosis Method Based on Fault Tree and Bayesian Networks. *Energy Procedia* **2012**, *17*, 1376–1382. [\[CrossRef\]](#)
57. You, B.; Lian, F.; Meng, X. An Analysis of Crash Factors for Freeways in Mountain Areas Based on Fault Tree and Bayesian Network. *J. Trans. Inf. Saf.* **2019**, *37*, 44–51.
58. Jun, H.-B.; Kim, D. A Bayesian network-based approach for fault analysis. *Expert Syst. Appl.* **2017**, *81*, 332–348. [\[CrossRef\]](#)
59. Ding, Y.; Zhang, M.; Qian, X.; Li, C.; Chen, S.; Wang, W. Using the geographical detector technique to explore the impact of socioeconomic factors on PM2.5 concentrations in China. *J. Clean. Prod.* **2019**, *211*, 1480–1490. [\[CrossRef\]](#)
60. Zhou, Y.; Kong, Y.; Sha, J.; Wang, H. The role of industrial structure upgrades in eco-efficiency evolution: Spatial correlation and spillover effects. *Sci. Total Environ.* **2019**, *687*, 1327–1336. [\[CrossRef\]](#)
61. Zerzour, O.; Gadri, L.; Hadji, R.; Mebrouk, F.; Hamed, Y. Semi-variograms and kriging techniques in iron ore reserve categorization: Application at Jebel Wenza deposit. *Arab. J. Geosci.* **2020**, *13*, 820. [\[CrossRef\]](#)
62. Yost, R.S.; Uehara, G.; Fox, R.L. Geostatistical Analysis of Soil Chemical Properties of Large Land Areas. I. Semi-variograms. *Soil Sci. Soc. Am. J.* **1982**, *46*, 1033–1037. [\[CrossRef\]](#)
63. Mazumdar, J.; Paul, S.K. Socioeconomic and infrastructural vulnerability indices for cyclones in the eastern coastal states of India. *Nat. Hazards* **2016**, *82*, 1621–1643. [\[CrossRef\]](#)
64. Singh, P.; Sharma, A.; Sur, U.; Rai, P.K. Comparative landslide susceptibility assessment using statistical information value and index of entropy model in Bhanupali-Beri region, Himachal Pradesh, India. *Environ. Dev. Sustain. A Multidiscip. Approach Theory Pract. Sustain. Dev.* **2021**, *23*, 5233–5250. [\[CrossRef\]](#)