

# A Deep Learning Based Approach to Examine the impact of Land Use Change on Shared Bicycles Usage in Rail Transit Stations

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**Abstract:** Due to China's booming economy and rapid urban expansion, significant progress has been made in the construction of rail transit (hereinafter referred to as RT), which is becoming an important means of connecting people in different urban areas, relieving urban traffic congestion and reducing environmental pollution. At the same time, the construction of rail transit will also affect the land use of the areas along the route, especially the mix of land use around the rail transit stations, and the mix of land use functions around the rail transit stations will affect the composition of the population around the stations, which in turn will affect the choice of feeder transport for passengers leaving the stations. From the perspective of environmental friendliness, low carbon and economic convenience, bicycle sharing is the best option to solve the problem of "last mile" to the destination after leaving the station, and its usage rate is the highest. Therefore, this study establishes a deep learning technology method to study the possibility of the impact of land use on shared bicycle usage within the influence range of rail transit stations. Firstly, the time-varying patronage of RT stations was predicted using cluster analysis and random forest method, then an evaluation system of the efficiency of shared units and RT interchange was constructed using AHP hierarchical analysis, followed by a vector machine model supported by least squares to study the relationship between land use and shared unit usage around RT stations. The results show that it is feasible to use deep learning techniques to study the impact of land use on bike-sharing usage within the area of influence of rail transit stations, and the case validation shows that an increase of 0.12 in the land use mix index at station A results in a 10.43% increase in share of shared bicycles in model choice, and an increase of 0.09 in the land use mix index at station B results in a 13.11% increase in share of shared bicycles in model choice. This indicates that with the development of rail transport and the increase in land use mix in the surrounding area, the share of shared bicycles in model choice is also increasing.

**Keywords:** land use change; rail transit station; shared bicycle

## 1 INTRODUCTION

With the rapid development of China's economy, key cities are expanding rapidly, causing a split in the spatial structure of cities, with some urban functions concentrated in the core areas while others are evacuated to new urban development areas. Rail transit (RT), as an efficient mode of transport, can effectively facilitate the interaction of people, logistics and capital flows between the core areas and the new urban development areas. At the same time, the development of rail transit also brings new opportunities for the development of land use along the route. Duan and Zhang [1] took the Xi'an Metro Line 2 in China as an example, and showed that rail stations have a significant impact on the land use of the 500 - 800 m area around the station, and that the mix of different functions around the station also affects the composition of the population around the station, which in turn affects the choice of transport connections for passengers leaving the station. Zhang [2], who introduced the choice of transport connections to urban rail stations, showed that the use of shared bicycles is the highest in terms of low carbon effect and economic cost. Therefore, how to establish the relationship between the mixed use of rail transit land and the utilization rate of shared bicycles is the key to exploring rail transit transfers.

At present, the connection problem of rail transit is a major challenge affecting the livability of the city. Research on the relationship between transportation systems and urban land use is an interdisciplinary subject, and its research focuses on urban geography and transportation geography, urban planning, transportation planning and other related fields. So far, the internal relationship, interaction mechanism and integrated development between the transportation system and urban land use have been deeply discussed at home and abroad from multiple perspectives such as theory, model, empirical evidence, planning practice and management.

The field of urban planning and transportation planning studies how to coordinate the relationship between the two and integrate development, etc., and is more directly oriented to practice. It is generally believed that the transportation system represents the supply system, and land use is the spatial aggregation of functions, representing the demand side. However, existing transportation infrastructure in urban built-up areas is insufficient and construction space is limited, resulting in a series of urban problems that are in a vicious cycle and are inconsistent with land use. At present, non-traditional transportation improvement measures can guide the intensive use of urban land and promote the full utilization of limited built-up area land resources, thereby achieving sustainable urban development. Shared bicycles are the best choice to solve the "last mile" problem after leaving the RT station to reach the destination. However, the current research on the impact of rail transit stations on the usage rate of shared bicycles is still relatively blank. Therefore, it is necessary to establish the relationship between rail transit stations and the usage rate of shared bicycles.

The influence of land use within the sphere of influence of a rail transit station on the usage rate of shared bicycles is confounded by many variable factors, such as the time-varying passenger flow of the rail transit station, different climatic conditions, the efficiency of the interchange between shared units and rail transit, and the land use mix are all variable factors. The aim of this paper is to investigate the possibility of using deep learning techniques to study the impact of land use on the usage rate of shared units within the sphere of influence of rail transit stations. Therefore, finding the main factors that affect the usage rate of shared bicycles at rail transit stations is an important starting point of this study.

In summary, the deep learning method analyzes the relationship between land use around rail transit stations and passenger flow, as well as the relationship between

land use around stations and the usage rate of shared bicycles. That is, this article first uses K-means algorithm to perform cluster analysis on passenger flow in different passenger transportation periods, and uses random forest and multifunctional LSTM (long and short-term memory) models to accurately explore the rules of passenger flow changing over time at rail transit stations. Then, the AHP analytic hierarchy process was used to construct an evaluation index system, and a vector machine model supported by the least squares method was used to explore the relationship between land use around the rail transit station and the usage rate of shared bicycles. Therefore, the purpose of this study is mainly as follows: (1) To establish an evaluation system for the transfer efficiency of shared bicycles and rail transit, and to obtain the relationship between land use around rail transit stations and the utilization rate of shared bicycles. (2) Use deep learning technology to predict the demand for shared bicycles at rail transit stations and arrange the number of shared bicycles scientifically and rationally.

## 2 LITERATURE REVIEW

Current research on the impact of rail transit on the periphery of stations mainly focuses on the following points: (1) is to explore the impact of urban rail transit on land use, and study the impact of land use on the traffic flow of urban rail transit and the balance of land use from the perspectives of land development intensity and mixed land use [3, 4]. (2) evaluates the impact of crime in communities near rail transit stations and the impact of surrounding business distribution from a sociological perspective [5, 6]. (3) uses evaluation methods to evaluate the current status and future trends of rail transit development. For example, by establishing a flexibility evaluation of the urban rail transit network to evaluate the responsiveness and coordination of rail transit in responding to future development. [7-9] explore the relationship between rail transit and urban development by assessing the construction risks of urban RT projects [10, 11]. In summary, most studies currently focus on the impact of rail transit itself on surrounding land use, and there are fewer studies on the impact of rail transit stations on the usage rate of shared bicycles in surrounding areas. In order to better connect the land use situation around rail transit with the use of shared bicycles, it is necessary to establish a transfer relationship between rail transit stations and shared bicycles.

Regarding how to establish the relationship between rail transit stations and shared bicycle transfers, current relevant research methods can be used for reference. In terms of research methods, relevant researchers mainly conduct relevant research based on a large amount of travel survey data. The research idea is mainly carried out through three parts: data survey collection - correlation analysis of target factors - analysis of results and giving predictions or strategies. For example, Vega and Reynolds-Feighan [12] used GIS visualization network technology to obtain travel data and carry out random simulations of residents' travel decisions. However, this method cannot dynamically learn the data. Bohte et al. [13] combined GIS technology, GPS data and other technologies to improve the accuracy of travel result

analysis. Although this method dynamically monitors travel, it cannot predict future needs. Currently, deep learning technology can effectively handle such problems. For example, Zhu et al. [14] combined deep learning theory and support vector machine to predict urban RT passenger traffic. Liu Lijuan proposed a new traffic passenger traffic prediction model based on deep learning method [15]. Zhan et al. [16] proposed a speed sensor for urban RT train speed measurement based on deep learning. Zhang et al. [17] proposed a deep learning architecture called convolutional network for short-term passenger traffic prediction of urban RT. Alawad et al. [18] used the depth learning method to assess the railway safety risks. It can be seen that deep learning technology has been widely studied and proved to have broad application prospects in predicting traffic flow. However, this study found that the relevant literature has not yet used deep learning methods to study the impact of RT on shared bicycle usage. Therefore, this study can predict the impact of RT on shared bicycle usage from both temporal and spatial aspects based on deep learning methods.

## 3 METHODOLOGY

### 3.1 Research Cases and Data Sources

This study selects Xi'an Beidajie Station (hereinafter referred to as Station A) and Xi'an Bell Tower Station (hereinafter referred to as Station B) as research cases. Beidajie Station and Bell Tower Subway Station are both important hub stations in Xi'an's subway system. Both subway stations are located in the core area of Xi'an, with Zhonglou subway station next to Bell Tower and Beidajie station located on Beidajie in the city center. The passenger flow and surrounding commercial activities of these two stations are very active, providing rich data and cases for research. Choosing these two stations as research cases not only provides an in-depth understanding of the operation and impact of Xi'an's subway system, but also enables comprehensive analysis from a wider range of urban transportation, commercial activities, historical and cultural protection, etc., which has important theoretical and practical implications significance. The average daily passenger flow of Station A was 36000 passengers in 2015, and the average daily passenger flow of Station B was 45000 passengers in 2015.

### 3.2 Data Sources

The travel data of Xi'an Bell Tower Station and Beidajie Station were obtained in 2020. The data comes from Xi'an Metro Company. Its data format is Csv file and is mainly used for forecasting the demand for shared bicycles. The shared bicycle data used in this study comes from Xi'an Big Data Center. This data set contains the shared bicycle order data of Hello Bicycle Company at Xi'an Bell Tower Station and Beidajie Station within 24 hours on June 6, 2020. The data includes user ID, trip start and end time, trip start and end longitude and latitude, trip start and end area, and travel time. and travel distance and other information, of which the number of borrowed and returned cars was 1562 times.

### 3.3 Research Framework

This study established an assessment model for the use of shared bicycles by land use around rail transit stations (Fig. 1). It is mainly divided into three parts: the first part, passenger volume prediction at rail transit stations based on deep learning technology. This paper first uses cluster analysis method to perform cluster analysis on passenger flows in different passenger transport periods, and uses the *K*-means algorithm to delineate passenger flow clusters in different passenger transport time series. The profile coefficient and Kalinsky-Harabaz index are used to determine the optimal clustering coefficient of inbound passenger volume at rail transit stations. Then, in view of the impact of different weather, this paper uses a normalization method to digitally transform weather characteristics, thereby eliminating prediction models of different orders of magnitude for inbound passenger traffic at rail transit stations. In terms of rail transit inbound passenger volume prediction model, this paper adopts random forest for feature selection and inputs the selected feature set into a multi-functional LSTM (long short-term memory) model. The multi-functional LSTM model can more accurately explore the rules of rail transit station passenger flow changing over time.

The second part is the evaluation system for the transfer efficiency between shared bicycles and rail transit. This paper establishes safety indicators, comfort indicators, convenience indicators and travel cost indicators to address the issue of the evaluation system for the transfer efficiency between shared bicycles and rail transit. And the AHP analytic hierarchy process is used to construct an

evaluation index system and an evaluation system to evaluate the transfer efficiency of shared bicycles and rail transit.

The third part is the relationship between land use at rail transit stations and shared bicycle utilization. This study is based on the passenger flow and shared bicycle utilization predicted above at rail transit stations, and combined with variables such as mixed land use, population employment rate, shared bicycle usage, and station passenger volume, using a vector machine model supported by least squares to analyze. In this way, the impact of mixed land use on the utilization rate of shared bicycles can be obtained.

Therefore, this study uses the above deep learning method to analyze the relationship between land use around rail transit stations and passenger flow, as well as the relationship between land use around stations and shared bicycle usage, to provide decision-making reference for urban planning layout and transportation organization.

### 3.4 Research Methods

#### 3.4.1 Passenger Traffic Prediction of Rail Transit Stations Based on Deep Learning Technology

The passenger traffic forecast framework is shown in Fig. 2. It is mainly divided into three parts: passenger transport mode analysis, construction of passenger transport aggregation characteristics, and inbound passenger volume prediction model.

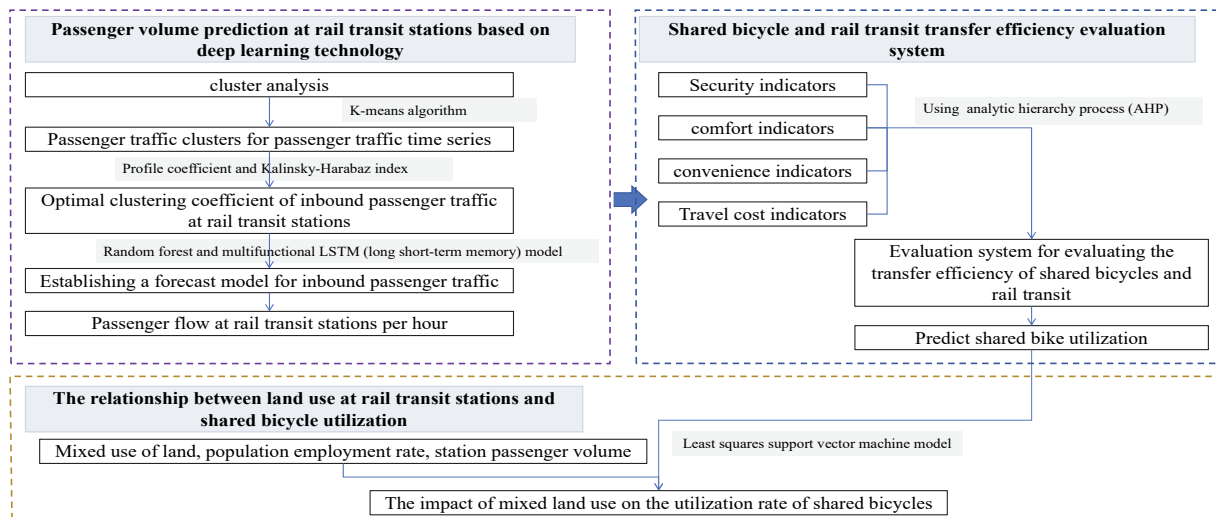


Figure 1 Research framework

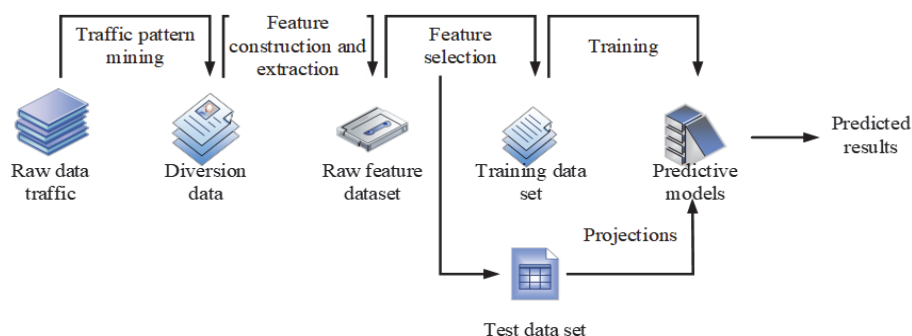


Figure 2 Passenger traffic forecasting framework

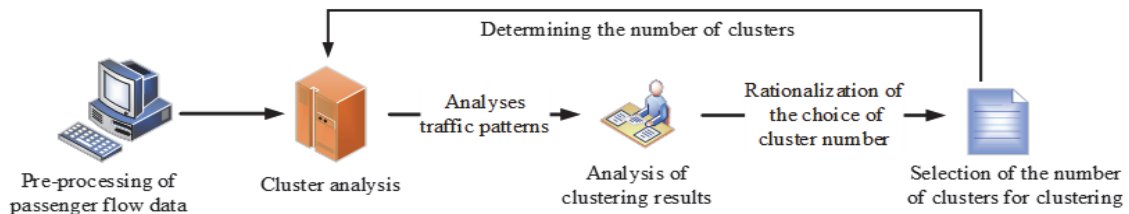


Figure 3 Key steps in passenger traffic pattern analysis

(1) Analysis of passenger traffic mode.

This paper selects the inbound passenger traffic figures of two typical stations, and analyzes the correlation between the passenger traffic figures of different figures. The passenger traffic figures of different figures in the same station are divided into different clusters, and each cluster represents a different passenger traffic structure. The  $K$  value is determined by the contour coefficient and the Calinski-Harabaz index, which are interpreted in combination with the actual passenger traffic, and the internal causes of its distribution are analyzed to ensure the rationality of clustering [19]. The main steps of passenger traffic analysis are shown in Fig. 3.

1) Clustering method.

If the rail passenger figures are clustered first, the similarity can be considered in the prediction model to improve the accuracy of the prediction results. Clustering analysis algorithms can be divided into partition based, hierarchical, dense, grid based and model-based methods. Although the methods of cluster analysis are different, the process of cluster analysis is the same, as follows:

- A. Figures preprocessing: this includes handling outliers and normalizing figures.
- B. Measurement of similarity: similarity measurement is a method to determine the similarity of samples, usually as a function of distance.
- C. Clustering: using the appropriate clustering algorithm and the appropriate similarity measure, the samples are classified according to the similarity measure.
- D. Evaluation of clustering results: evaluation indexes are used to evaluate the clustering results to determine the effectiveness of clustering results.
- E. Description of clustering results: the validity of clustering results is determined by connecting the clustering results with the actual problems for interpretation.

2)  $K$ -Means algorithm.

The  $K$ -Means algorithm is a widely used unsupervised learning cluster analysis method. Its main goal is to make the points within each cluster as similar as possible and the points between different clusters as different as possible. It has good scalability for processing large data sets, so it is beneficial to the deep learning cluster analysis of this study.  $K$ -Means algorithm ( $K$ -means clustering algorithm) is a partition based method. It first divides the set into  $K$  clusters, then determines the cluster center of each cluster, calculates the distance between each sample and the cluster center, and then divides the set into  $K$  clusters according to the distance, creates a new cluster center according to the average characteristics, compares it with the original cluster center, and iterates until the cluster center does not change any more [20]. The specific clustering steps of passenger traffic figures are as follows:

- A. From  $N$  passenger traffic time series,  $K$  passenger traffic time series are selected as the initial cluster center for clustering.
- B. For each passenger traffic time series in the cluster, the distance from each cluster center is calculated, and the passenger traffic time series is divided into the cluster where the nearest cluster center is located.
- C. The new cluster center (passenger traffic time series) of each cluster is recalculated.
- D. The distance between the new cluster center and each passenger time series is calculated, and the above steps are repeated until the standard measurement function converges. In this case, the algorithm is completed, otherwise it returns to point B.

The essence of  $K$ -Means algorithm is to update the cluster center in each iteration until the iteration goal is reached. The iteration goal is to minimize the quadratic error defined in the formula, as defined in the formula:

$$F = \sum_{i=1}^k \sum_{a \in c_i} dist(\mu_i, a)^2 \tag{1}$$

Among them,  $\mu_i$  represents the center of gravity of the  $i$ th group,  $c_i$  represents the  $i$ th group,  $dist(\mu_i, a)^2$  measures the distance between the passenger traffic time series of a certain date and the group center, and the calculated value represents the correlation between the figures.

Euclidean distance is usually used to measure the spatial distance between samples, and is suitable for measuring the similarity between passenger traffic time series. Therefore, Euclidean distance is used as the similarity measurement of  $K$ -Means.

$$dist(\mu_i, a) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \dots + (a_n - b_n)^2} \tag{2}$$

3) Selection of cluster family.

The best search range of clustering is  $[2, int \sqrt{n}]$ , that is,  $C_{min} = 2$  and  $C_{max} = int \sqrt{n}$ . The number of figure sets used in this paper is 36, so the search range of clustering is [2.5].

Based on the fact that the figures in the sample can be effectively clustered, people can evaluate whether the number of clusters is reasonable. The main methods to evaluate the clustering effect are pre-clustering method, stability method, index method and system development method. In this paper, through comparative analysis, the index method is used to determine the number of groups. It is a simple and effective method, which is suitable for selecting clusters to group the time series of passenger traffic.

Currently, silhouette coefficient and Kalinsky-Harabaz index are two common methods to test the

rationality of cluster analysis. Silhouette coefficient is to verify the feasibility of cluster analysis, and the Kalinsky-Harabaz index is a rationale for analyzing clustering effects. Therefore, in this paper, two internal indicators, namely profile coefficient and Calinski-Harabaz index, are used to determine the optimal clustering number of inbound passenger traffic at each station.

A. Profile factor.

For a sample  $i$ , its profile coefficient is given by the formula:

$$S(i) = \frac{y-x}{\max(x,y)} \tag{3}$$

The value range of profile coefficient is  $[-1, 1]$ . The larger the value of profile coefficient, the closer the sample is to the figures of the same cluster than to the figures of different clusters, so the classification is more effective. The closer the contour coefficient is to zero, the more it indicates that clustering is not feasible, and several clusters that are close to each other must be merged.

B. Calinski-Harabaz index.

The larger the Calinski-Harabasz value obtained, the smaller the covariance of figures in a cluster. The greater the covariance between different clusters, the more obvious the boundary between clusters, and the better the clustering effect. The formula is as follows:

$$s(k) = \frac{tr(B_k) m-k}{tr(W_k) k-1} \tag{4}$$

Among them,  $m$  is the number of samples,  $k$  is the number of categories,  $B_k$  is the covariance matrix between categories,  $W_k$  is the covariance matrix within categories, and  $tr$  is the trace of the matrix.

(2) Construction of passenger traffic aggregation characteristics.

1) Proximity in time.

The passenger traffic at the current time is affected by the passenger traffic in the previous  $n$  periods. People can select the passenger traffic figures of  $n$  periods before the destination time to predict the destination time.

The passenger traffic arriving at the destination at the predicted time ( $t$  time every day) is called  $x_{i,d}(t)$ . The inbound passenger traffic at the first two times of the predicted time is expressed as  $x_{i,d}(t-1)$ ,  $x_{i,d}(t-2)$ ,  $x_{i,d}(t-3)$ , ...,  $x_{i,d}(t-n_i)$ , which are used as the approximate time characteristics of the passenger traffic arriving at the destination station  $i$  at the predicted time ( $t$  time of the  $d$  day) [21].

2) Classification of passenger traffic time.

The inbound passenger traffic has different characteristics in different periods, so the direct use of all day figures for prediction is not effective. For the same passenger traffic mode,  $K$ -Means clustering algorithm can be used to divide the passenger traffic period, as shown below.

A. Each day is divided into 36 periods (5:00 - 23:00). Each passenger traffic model corresponds to an interval of 30 minutes. The passenger traffic figures in November 2021

are processed into the set  $\{x_1, x_2, \dots, x_{36}\}$  of passenger traffic samples. Among them, the vector  $x_i$  of passenger traffic represents the  $i$  th period;

B. The initial clustering center is randomly selected from the passenger traffic time series;

C. The Euclidean distance between each passenger traffic time series and the cluster center is calculated, and the clusters are reordered according to the similarity index;

D. The location of each cluster center is recalculated;

E. When the maximum number of iterations/termination condition is reached, it stops; otherwise, C and D are repeated.

A category based variable is used to arrange passenger traffic time, and  $T_d(t) = n$ . Among them,  $n$  is the  $n$ th passenger traffic time category.

3) Cyclical characteristics of passenger transport,

People have gradually formed the habit of choosing travel mode and time. Therefore, for rail transport, the development of passenger traffic volume has certain regularity and periodicity.

A. Day periodicity,

The inbound passenger traffic at the scheduled time ( $t$  time every day) of target station  $i$  is expressed as  $x_{i,d}(t)$ , and the inbound passenger traffic at the same time two days before the predicted time is expressed as  $x_{i,d-1}(t)$ ,  $x_{i,d-2}(t)$ ,  $x_{i,d-3}(t)$ , ...,  $x_{i,d-n_d}(t)$ . These passenger traffics are the characteristics of the inbound passenger traffic of the target station  $i$  at the scheduled time.

B. Weekly periodicity

The inbound passenger traffic of the target station  $i$  at the scheduled time ( $t$  time every day) is represented by  $x_{i,d}(t)$ . The inbound passenger traffic of the same day two weeks before the scheduled time is represented by  $x_{i,d-7}(t)$ ,  $x_{i,d-14}(t)$ ,  $x_{i,d-21}(t)$ , ...,  $x_{i,d-7n_w}(t)$ . These passenger traffics are the weekly cycle characteristics of the inbound passenger traffic of the target station  $i$  at the scheduled time.

4) Weather factor.

The meteorological factors of target station  $i$  at the forecast time ( $t$  time per day) are expressed by  $c(d)$ , and their quantification methods are shown in Tab. 1.

Table 1 Weather conditions

| Weather conditions | $c(d)$ |
|--------------------|--------|
| Sunny              | 0      |
| cloudy             | 1      |
| Light rain         | 2      |
| Moderate rain      | 3      |
| Heavy rain         | 4      |
| Showers            | 5      |
| Thunder showers    | 6      |
| Haze               | 7      |

The temperature of the predicted time (time  $t$  of day  $d$ ) of target station  $i$  is expressed in  $te(d)$ . Among them,  $te(d)$  is the average of the lowest and highest temperatures of each day.

The wind of target station  $i$  at the prediction time (time  $t$  on day  $d$ ) is expressed by  $w(d)$ , and its quantification method is shown in Tab. 2.

**Table 2** Wind power quantification table

| Wind power     | $w(d)$ |
|----------------|--------|
| $\leq 3$ level | 0      |
| Level 3        | 1      |
| Level 4        | 2      |
| Level 5        | 3      |
| Level 6        | 4      |

5) Pretreatment of passenger traffic correlation characteristics.

The above features are constructed and extracted from the relevant features of passenger traffic, but cannot be directly used as the input of the model. These features have two main problems: some digital features do not belong to the same scale, such as passenger traffic and temperature, which cannot be directly compared; for category based features, such as passenger traffic time, there is no dimensional relationship between their attributes. Quantization is only for classification, so the quantized value cannot be directly used as the input figures of the feature. Aiming at the above problems, this paper adopts the normalization method to solve these problems [22].

Normalization is a form of figures conversion, which involves converting figures so that it falls within a given range, thus eliminating the impact of different orders of magnitude on the prediction results. In this paper, the maximum minimum normalization calculated by the formula is used.

$$y' = \frac{y - y_{\min}}{y_{\max} - y_{\min}} \quad (5)$$

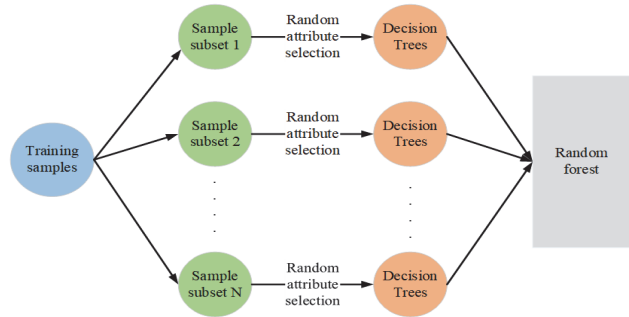
In the formula,  $y$  is the original feature figures;  $y'$  is the processed characteristic figures;  $y_{\max}$  and  $y_{\min}$  are the maximum and minimum eigenvalue respectively.

(3) Forecast model of inbound passenger traffic.

Currently, deep learning technology uses decision trees to establish learning algorithms, and for big data, long and short-term memory models need to be established to handle various data processing processes such as data training, simulation, and monitoring. Therefore, in this paper, random forests are used for feature selection, and the selected feature set is input into the multi-functional LSTM (Long Short Term Memory) model. The multi-functional LSTM model can more accurately explore the rule of historical attributes of passenger traffic network changing with time, and reduce the complexity of multi-functional LSTM network to a certain extent.

1) Feature selection method based on random forest.

Random forest is a typical representative of comprehensive feature selection algorithm, which is suitable for modeling nonlinear features. The passenger related figures is a time series with nonlinear characteristics. Therefore, the random forest method is not only easy to achieve feature selection, but also does not need too much debugging. The random forest algorithm uses both figures samples and feature samples. The use of these two types of random samples makes the algorithm more versatile and feature selection easier [23]. In this paper, random forests are used to reduce the complexity of prediction networks. The schematic diagram of random forest is shown in Fig. 4.



**Figure 4** Construction diagram of a random forest

The establishment process is as follows:

- A. In the original figures, the random guidance method is used to extract  $n$  samples to create  $N$  training sets. These  $n$  samples are root node samples, and  $N$  training sets train  $N$  decision tree models;
- B. For each decision tree model, when each node is partitioned,  $m$  attributes are randomly selected from  $M$  attributes in the sample, and then an attribute is selected for each partition according to the information gain, which is used as the attribute of the node to be partitioned;
- C. The method  $B$  is applied to partition each node in the decision tree until it is no longer partitioned, thus forming a decision tree without pruning operation;
- D. The above steps are repeated to create multiple decision trees and generate a random forest for prediction or classification.

2) RF-LSTM model.

This paper constructs a LSTM prediction model based on random forests (RF-LSTM model), in which the LSTM model is a multi feature LSTM model. The structure of RF-LSTM prediction model is shown in Fig. 5.

The process of forecasting inbound passenger traffic is as follows:

- A. The relevant attributes of passenger traffic are randomly sampled. The selected figures are the figures in the input bag, and the unselected figures are the figures in the output bag;
- B. The random forest is used to model the figures in the bag. Each tree in the random forest has a figures error outside the bag, which can be used to test the efficiency of the model. Therefore, the corresponding figures error outside the bag  $err_{OOB1}$  of the model is calculated;
- C. The characteristic value of passenger traffic at a certain point is changed randomly, that is, noise is added randomly, and the out of bag figures error  $err_{OOB2}$  of the random forest model is recalculated;
- D. If there are  $n$  trees in the random forest, the importance of each passenger traffic characteristic is calculated. The calculation method of importance is as follows:

$$VI = \sum (err_{OOB2} - err_{OOB1}) / n \quad (6)$$

- E. Different passenger traffic characteristics are sorted by importance;
- F. The unimportant passenger traffic features are deleted, and a group of features are obtained after the features are selected;
- G. The selected feature set is input into the multi-functional LSTM model to predict the inbound passenger traffic.

This section uses deep learning techniques to forecast passenger traffic at rail stations, starting with passenger modal analysis, followed by the construction of passenger

aggregation features, and ending with an inbound passenger traffic forecasting model.

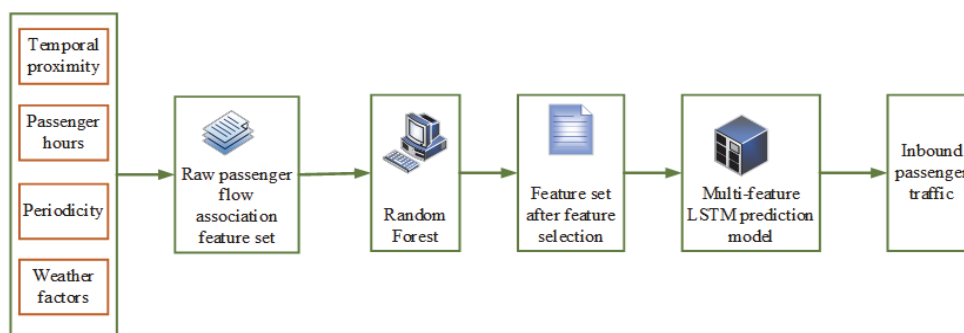


Figure 5 Structure of the RF-LSTM prediction model

### 3.4.2 Shared Bicycle and Rail Transit Transfer Efficiency Evaluation System

Based on the needs of tourists, this paper analyzes the factors that affect the selection of B + R hub, establishes an evaluation system, evaluates the existing hub, finds out the weaknesses of the hub, improves the service capacity of the established bicycle rental facilities, and provides a theoretical basis for the proposed bicycle lane planning, location of bicycle rental facilities, and B + R hub. At the same time, it also provides a theoretical basis for the planning of shared single lane, the location of shared bicycle facilities and the organization of B + R centers [24].

(1) Building evaluation index system.

The factors influencing the choice of shared bicycles and rail transit transfer (hereinafter referred to as B + R) mainly include three aspects: the characteristics of B + R traffic organization, including convenience, accessibility, speed, comfort, cost, etc; characteristics of individual travelers, including traffic ownership, gender, age, income, occupation, etc; the characteristics of travel, including departure and destination. The main problem to be solved by urban transport is to transport people rather than vehicles. From the perspective of environment, energy conservation and sustainable development, public transport is the main role of urban transport. However, the mode of travel is the result of personal choice. As a pillar of the city, public transport should improve its service level

in terms of objective software and hardware, meet residents' travel needs for convenience, safety and comfort, and guide more travelers to choose public transport at economic cost to form a scientific and reasonable urban transport structure [25].

The process is based on the transfer process of residents after completing RT, including three connections: connecting residents from the departure and destination to the bike sharing rental station, riding the bike sharing rental station, and connecting the bike sharing rental station to the entrance and exit stations. This article analyzes the factors that affect the transfer efficiency of residents in these three parts, selects indicators to evaluate exchange efficiency, and establishes an evaluation framework system. The main factors are reflected in four aspects: safety, comfort, convenience and travel cost [24]. Convenience mainly involves the layout of facilities and the efficiency of transfer transportation. Therefore, the density of shared bicycle lane network, accessibility of rental points, capacity of rental points, shared channels and sharing conditions are the basis for equipment evaluation. At the same time, shared bicycle information, borrowed bicycle usage time, transportation space connectivity, and ticket purchase linkage are the main factors affecting the transfer transportation organization.

Table 3 Evaluation system for the efficiency of bike-sharing and rail transit interchange

|                                                           |                                      |                                                          |                                                        |
|-----------------------------------------------------------|--------------------------------------|----------------------------------------------------------|--------------------------------------------------------|
| Bicycle sharing and rail transit interchange efficiency B | Convenience and ease B1              | Facilities B1                                            | Bike-sharing lane network density B111                 |
|                                                           |                                      |                                                          | Accessibility of bike-sharing rental points B112       |
|                                                           |                                      |                                                          | Bicycle sharing rental point interchange capacity B113 |
|                                                           |                                      |                                                          | Bicycle sharing access B114                            |
|                                                           |                                      |                                                          | Bicycle sharing condition B115                         |
|                                                           | Interchange traffic organization B12 | Guidance information for bike-sharing rental points B121 |                                                        |
|                                                           |                                      | Average interchange time B122                            |                                                        |
|                                                           |                                      | Pedestrian interchange B123                              |                                                        |
|                                                           | Safety B2                            | The state of segregation of bicycle sharing lanes B21    |                                                        |
|                                                           | Comfort B3                           | Comfort during interchange B31                           |                                                        |
| Reasonable fees B4                                        |                                      |                                                          |                                                        |

In terms of safety, it mainly comes from the mutual interference between shared bicycles and other modes of transportation. Therefore, the isolation status of shared

bicycle lanes is the most effective indicator for judging safety. The impact of rail transit on the comfort of shared bicycles depends on the convenience of the space

intersection, so the comfort of the intersection is its biggest influencing factor. Reasonable costs use the management costs invested in transferring shared bicycles and rail transit to represent their daily operating costs. In summary, the evaluation system for the transfer efficiency between shared bicycles and rail transit is shown in Tab. 3

(2) Revising the index weight according to the analytic hierarchy process.

The AHP method is used to create an evaluation indicator system and a system to evaluate the efficiency of shared bicycles and RT transfers.

A. Hierarchy establishment

In this paper, a three-layer evaluation framework is developed. The transfer efficiency  $B$  of shared bicycles and RT is the target layer, the convenience standard layer is  $B_i$ , and the facility support  $B_{ij}$  is the indicator layer.

B. Constructing judgment matrix.

$$B = \begin{bmatrix} b_{11} & \cdots & b_{14} \\ \vdots & \ddots & \vdots \\ b_{41} & \cdots & b_{44} \end{bmatrix} \quad (7)$$

The sum of elements in each line of the judgment matrix is calculated, which is recorded as  $V_i$ :

$$V_i = \sum_{j=1}^n b_{ij} \quad (8)$$

The relative weight  $W_i$  of each element of a single standard can be determined by normalization  $V_i$  (shown as the eigenvector of the matrix):

$$W_i = \frac{V_i}{\sum_{i=1}^n V_i} \quad (9)$$

C. Consistency inspection.

Consistency check checks the appropriateness of the matrix by calculating the consistency coefficient. If the consistency requirements are not met, the estimation matrix shall be modified as follows:

The maximum eigenvalue  $\lambda_{\max}$  of the judgment matrix is calculated:

$$\lambda_{\max} = \sum_{i=1}^n \frac{(BW)_i}{nW_i} \quad (10)$$

Consistency indicators are calculated:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (11)$$

The consistency ratio is  $CR = CI/RI$ . When it is  $CR < 0.1$ , the judgment matrix meets the consistency test.

D. Weight checking.

The expert evaluation method is used for comparison and evaluation, and the results are adjusted. Four matrices are established to test the consistency. The weight of each goal on the total goal is calculated, and the results are shown in Tab. 4.

Table 4 Indicator weighting values

| Indicators                                          | Weighting values |
|-----------------------------------------------------|------------------|
| Bike-sharing lane network density                   | 0.018            |
| Accessibility of bike-sharing rental points         | 0.101            |
| Bicycle sharing rental point interchange capacity   | 0.103            |
| Bicycle sharing access                              | 0.049            |
| Bicycle sharing condition                           | 0.076            |
| Guidance information for bike-sharing rental points | 0.015            |
| Average interchange time                            | 0.078            |
| Pedestrian interchange                              | 0.036            |
| Ticketing intermodal                                | 0.041            |
| The state of segregation of bicycle sharing lanes   | 0.092            |
| Comfort during interchange                          | 0.051            |
| Reasonable fees                                     | 0.34             |

This section constructs an evaluation system for the efficiency of bike-sharing and rail transit interchange, including the construction of the evaluation index system and the determination of the evaluation index weights. The relationship between shared bicycle and rail transit interchange and station passenger flow is closely related, and the relationship between share of shared bicycles in model choice and station passenger flow can be calculated through the study of interchange efficiency.

3.4.3 Relationship between Surrounding Land Use and Passenger Traffic Characteristics of Rail Transit Stations

The mixed use of land in the station cluster area is widely considered as an important factor affecting the number of tourists in the station. The degree of mixed land use refers to the overall situation of mixed land use in a specific area of a city, that is, the use of multiple types of land. It is usually measured by the entropy index. The higher the entropy index, the better the land use [26].

(1) Model variables.

1) Dependent variable.

The dependent variable analyzed in this paper is the change of station traffic volume due to the change of land use and population proportion. Its size is affected by the following factors: i the total number of jobs in the station cluster area; ii post distribution; iii the proportion of stations in the overlap area.

Therefore, in order to separate the impact of mixed land use and the proportion of employed population in the station cluster on passenger traffic, people must first normalize the impact of these three factors on passenger traffic. The ratio of station passenger traffic to weighted population is calculated according to the following formula:

$$\rho = \frac{S}{P_{weight}} \quad (12)$$

In the formula:  $\rho$  is the dependent variable of this article;  $S$  is the passenger traffic of the station;  $P_{weight}$  is the population in the passenger traffic coverage area of the station, which is weighted by the decreasing weight and the population proportion in the overlapping area with the adjacent station.

2) Land use mixing degree and post resident population ratio.

The mixed degree of land use can be expressed by the entropy index which expresses the diversity of land use. The entropy index of land use diversity varies from 0 to 1. The larger the value, the stronger the land use diversity. In this article, post types are used instead of different land use types. The formula for determining the degree of land use mix is as follows:

$$m_{ix} = \frac{-\sum_{j=1}^k q_j \ln(q_j)}{\ln k} \quad (13)$$

In the formula,  $m_{ix}$  is the entropy index of land use mixing degree;  $q_j$  is the proportion of the  $j$ th type of work in the total number of work;  $k$  is the total number of work types.

The ratio of jobs to permanent residents refers to the ratio of the number of jobs to the number of permanent residents in the attraction area of the station, which is used to evaluate the balance between jobs and permanent residents in the passenger attraction area.

(2) Least squares support vector machine model.

The least squares method and support vector machine (SVM) are both important algorithms widely used in machine learning and data analysis. The least squares method is a commonly used method for estimating unknown parameters from observed data while minimizing the variance between predicted and actual values. Support vector machine is a powerful learning algorithm that can be used for classification and regression problems by finding the optimal hyperplane to classify data into different categories. Because this study cannot determine whether there is a direct linear relationship between the mixed use of land, population employment rate and dependent variables within the station, it combines these two algorithms to establish the relationship between variables to improve the accuracy of prediction.

It is impossible to determine whether there is a direct linear relationship between the mixed use of land, population employment rate and the dependent variables within the station. Therefore, this paper uses the vector machine model supported by the least squares method to regress the relationship between the above variables.

The basic idea of support vector machine is to use pre selected nonlinear application input vectors in a high-dimensional feature space, and build an optimal decision function in this space. The least squares support vector machine uses the linear least squares system as the loss function, rather than the traditional quadratic programming method used in the reference vector machine. The error square  $\varepsilon$  between the output value of the model and the actual output value is taken as the loss function, and its formulas are as follows:

$$\min J(\delta, \varepsilon) = \frac{1}{2} \delta \cdot \delta + c \sum_{i=1}^l \varepsilon_i^2 \quad (14)$$

$$y_i = \varphi(x_i) \cdot \delta + d + \varepsilon_i \quad (15)$$

In the formula,  $x_i$  is the input variable of the  $i$ th station sample;  $y_i$  is the output variable of the  $i$ th station sample;  $\varepsilon_i$  is the error between the output value of the  $i$ th station model and the actual output value;  $\delta$  is the complexity weight of the model;  $d$  is the threshold of the model;  $l$  is the number of station samples.

The Lagrangian method is used to solve this minimization optimization problem with constraints:

$$L(\delta, d, \varepsilon, a, \gamma) = \frac{1}{2} \delta \cdot \delta + c \sum_{i=1}^l \varepsilon_i^2 - \sum_{i=1}^l a_i (\varphi(x_i) \cdot \delta + d + \varepsilon_i - \gamma_i) \quad (16)$$

There are:

$$\frac{\partial L}{\partial \delta} = 0 \rightarrow \delta = \sum_{i=1}^l a_i \varphi(x_i) \quad (17)$$

$$\frac{\partial L}{\partial d} = 0 \rightarrow \sum_{i=1}^l a_i = 0 \quad (18)$$

$$\frac{\partial L}{\partial \varepsilon_i} = 0 \rightarrow a_i = c \varepsilon_i \quad (19)$$

$$\frac{\partial L}{\partial a_i} = 0 \rightarrow \delta \varphi(x_i) + d + \varepsilon_i - \gamma_i = 0 \quad (20)$$

Eq. (6) to Eq. (9) are substituted into Eq. (5), and  $\varepsilon_i$  and  $\delta$  are deleted to obtain the form of least squares support vector machine. Kernel function  $K(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j)$  is defined and the nonlinear formula is obtained:

$$f(x) = \sum_{i=1}^l a_i K(x_i, x_j) + b \quad (21)$$

This section examines the relationship between land use and passenger traffic characteristics around rail stations, which, when combined with the previous two sections, allows the relationship between land use and share of shared bicycles in model choice around rail stations to be calculated.

## 4 EVALUATION ON THE IMPACT OF LAND USE EVOLUTION ON SHARED BICYCLES WITHIN THE SCOPE OF RAIL TRANSIT STATION

### 4.1 Result Analysis

Regarding the evaluation of the impact of land use evolution within rail transit stations on shared bicycles, first, select two stations named A and B, and use the deep learning technology constructed in this study to predict the passenger flow of RT stations in 2015 and 2021. Then the utilization rate of shared bicycles is calculated based on the transfer efficiency between shared bicycles and RT. Based on the relationship between RT land use and passenger transport characteristics, and combined with the transfer rate of shared bicycles, this study analyzes the impact of RT land use on shared bicycle utilization. The specific results are as follows.

### 4.2 Rail Transit Station Passenger Volume Prediction Results Based on Deep Learning Technology

The daily average passenger traffic forecast results of RT stations in 2015 and 2021 are shown in Fig. 6.

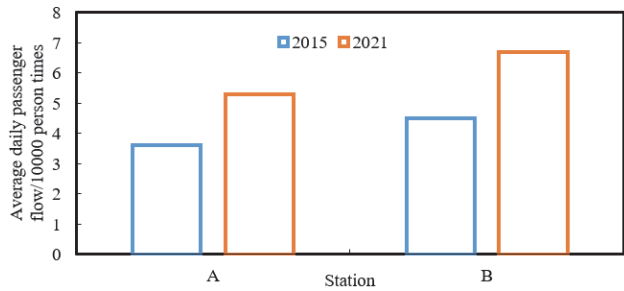


Figure 6 Forecast results of average daily passenger traffic of rail transit station

It can be seen from the figures that the average daily passenger traffic of station A would increase from 36000 in 2015 to 53000 in 2021, and that of station B would increase from 45000 in 2015 to 67000 in 2021. The change of passenger traffic at RT stations is not only affected by population factors, but also has a greater relationship with land use change within the scope of RT stations.

### 4.3 The utilization Rate of Shared Bicycles Based on the Simulation of Shared Bicycles and Rail Transit Transfer Efficiency Evaluation

Based on the B + R transfer efficiency evaluation index system in Chapter 4.3 and the average daily passenger flow of the RT station, we calculated the utilization rate of shared bicycles at the two stations in 2015 and 2021, as shown in Fig. 7.

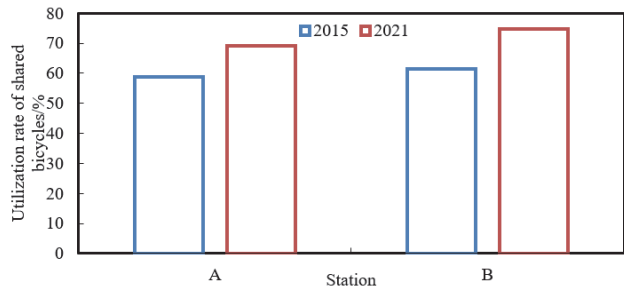


Figure 7 Share of shared bicycles in model choice in the station

In 2015, the share of shared bicycles in model choice at station A was 58.74%, and in 2021, the utilization rate would increase to 69.17%. The share of shared bicycles in model choice in station B was 61.58% in 2015 and 74.69% in 2021. It can be seen from the figures that with the increase of the average daily passenger traffic of RT stations, the utilization rate of shared bicycles outside the stations is also gradually improving.

(3) The relationship between land use of RT stations and the share of shared bicycles in model choice.

The land use entropy indexes of the two stations in 2015 and 2021 are shown in Fig. 8.

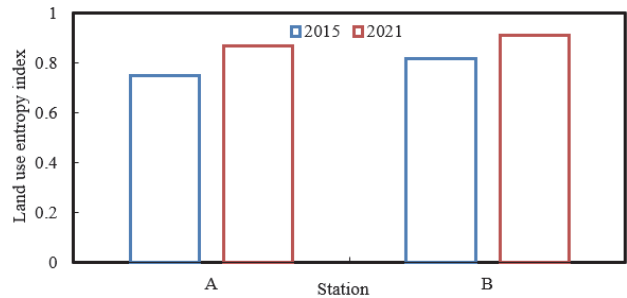


Figure 8 Land use mix index

The land use entropy index of station A was 0.75 in 2015 and 0.87 in 21. The land use entropy index of station B was 0.82 in 2015 and 0.91 in 2012. The land use of the two stations has gradually improved, the average daily passenger traffic of RT stations has also increased, and the share of shared bicycles in model choice has also increased. The land use entropy index of station A increased by 0.12, and the share of shared bicycles in model choice increased by 10.43%; the land use entropy index of station B increased by 0.09, and the share of shared bicycles in model choice increased by 13.11%. It shows that improving the land use of the station can effectively improve the passenger traffic of the station, thereby improving the share of shared bicycles in model choice.

## 5 DISCUSSION

This study explores the issues of urban function and transportation optimization from a new perspective. Currently, there are few studies on the benefits of mixed land use on urban planning and transportation organization in the existing literature. This study will add to the research gap in this area. This study focuses on the prediction of rail transit traffic volume and the usage of shared bicycles in the surrounding areas, and establishes deep learning technology to quantitatively study the relationship between the demand for shared bicycles and land use. This paper attempts to explore the internal driving mechanism between mixed land use and the demand for shared bicycles in order to explore the impact of land use strategies around rail transit on the dynamic balance of shared bicycles, and to further use this as a theoretical basis for the interrelationship between future urban planning and transportation organization. Therefore, the results of this study can enrich the theory and method system of the dynamic balance of transportation and land use distribution.

Judging from the results, with the development of rail transit and the increase in surrounding land use mix, the utilization rate of shared bicycles is also increasing. For example, the land use mixing index of station A increased by 0.12, and the shared bicycle utilization rate increased by 10.43%. The land use mixing index of station B increased by 0.09, and the shared bicycle utilization rate increased by 13.11%. Therefore, this result can provide a theoretical basis for the planning of proposed bicycle lanes and the location selection of bicycle rental facilities. It also provides a theoretical basis for the planning of shared bicycle lanes, the location of shared bicycle facilities, and the organization of B + R centers [19]. At the same time, it provides data support to improve the service capabilities of established bicycle rental facilities.

The research in this article still has some shortcomings. First of all, this study only uses the perspective of shared bicycles to explore the issue of rail transit transfers, which has certain limitations. Follow-up research can provide a comprehensive analysis of the dynamic balance impact of transfers based on public transportation systems, private transportation systems, etc., on the distribution of rail transit passenger flow. Secondly, this study simplifies the indicators of the impact of mixed land use on shared bicycle utilization. For example, this study has room for further optimization in the selection of weather factors and mixed land use factor indicators. This issue can be explored in future research.

## 6 CONCLUSIONS

With the rapid development of rail transit, the land use mix around stations is getting higher and higher, thus affecting the share of shared bicycles in model choice. From the perspective of environmental protection, low carbon and economic convenience, shared bicycles are the best choice to solve the "last mile" to the destination after leaving the RT station. This study reveals the relationship between the two. The specific results are as follows.

In this paper, the share of shared bicycles in model choice is obtained by predicting the passenger volume of rail transit stations using deep learning techniques and constructing an evaluation system for the efficiency of bicycle sharing and rail transit interchange. Then, the characteristics of land use around rail transit stations and passenger traffic at rail transit stations are analysed, and the relationship between land use around rail transit stations and the share of shared bicycles in model choice is derived by combining the findings of the above two parts of the study. This study provides a scientific prediction method for the transfer relationship between rail transit stations and shared bicycles.

The findings of this paper show that it is possible to implement the purpose of this paper's research using deep learning techniques, demonstrating that it is possible to study the impact of land use evolution on bike-sharing usage within the sphere of influence of rail transit stations using deep learning techniques. The final case experiment results show that with the development of rail transit construction, the increasing land use mix around rail transit stations will promote the share of shared bicycles in model choice. It can be seen that scientifically arranging the land use of the plot can improve the economic value and resource utilization efficiency of the entire plot.

This study aims at the effective integration of transportation planning and urban land use. However, in fact, land use and transportation planning are two tasks that tend to be separated, which makes the utilization rate and mobility of road traffic unable to be effectively connected with land use behavior. This study establishes an analytical framework based on the relationship between land use and shared bicycle usage to provide scientific decision-making for transportation planning and the combination of urban land use.

Transportation transfer issues profoundly affect urban livability. Exploring urban spatial structure and land mixed use optimization to alleviate traffic problems is an effective way to solve the separation of urban planning and

transportation planning. This study only uses the perspective of shared bicycles to explore the relationship between land use and traffic flow, which has certain limitations. The rational allocation of urban structure and transportation organization requires comprehensive consideration of government policies, transportation planning organization, management methods and other factors. This study has only solved a small part of the problem, and there is still a long way to go to explore transportation-friendly and livable cities.

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