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Analysis and Prediction Model of Resident Travel Satisfaction

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Abstract: To promote the sustainable development of urban traffic and improve resident travel satisfaction, the significant factors affecting resident travel satisfaction are analyzed in this paper. An evaluation and prediction model for travel satisfaction based on support vector machine (SVM) is constructed. First, a multinomial logit (MNL) model is constructed to reveal the impact of individual attributes, family attributes and safety hazards on resident travel satisfaction and to clarify the significant factors. Then, a travel satisfaction evaluation model based on the SVM is constructed by taking significant factors as independent variables. Finally, travel optimization measures are proposed and the SVM model is used to predict the effect. Futian Street in Futian District of Shenzhen is taken as the object to carry out specific research. The results show that the following factors have a significant effect on resident travel satisfaction: age, job, level of education, number of car, income, residential area and potential safety hazards of people, vehicles, roads, environment, etc. The model fitting accuracy is 87.76%. The implementation of travel optimization measures may increase travel satisfaction rate by 14.07%.

Keywords: resident travel; satisfaction; support vector machine; travel optimization; policies and measures

1. Introduction

With the rapid development of economy and society, the number of motor vehicles is increasing yearly. Likewise, the proportion of residents relying on cars for travel has been increasing, which is leading to increasingly serious congestion of urban roads and the frequent occurrence of various travel-safety problems. These problems greatly reduce resident travel satisfaction. Traffic safety is a crucial part of urban safety. “Opinions on Promoting Urban Safety Development” was issued by the General Office of the State Council of the Communist Party of China in January 2018 [1]. This publication pointed out that it is necessary to strengthen the construction of urban traffic infrastructure, optimize the urban road network and traffic organization, set and improve the traffic facilities scientifically and standardly, etc. It can be seen that China attaches great importance to traffic safety. Today, China vigorously advocates “green travel”, so how to provide residents a safe, efficient and convenient travel environment is the common goal of many researchers in the field of transportation. By analyzing the hidden safety hazards in “people, cars, roads and environment” and mining the significant factors affecting resident travel satisfaction, the travel environment can be optimized in a targeted way to ensure residents’ travel safety and improve their travel satisfaction. Meanwhile, it can provide a certain reference for formulating traffic policies and allocating resources reasonably.

2. Literature Review

Domestic and foreign scholars have done much research on the evaluation of resident travel satisfaction. Some scholars have analyzed the overall satisfaction of residents with urban traffic: Karen

Thompson et al. [2] took Manchester as an example to study the various dimensions of overseas tourists' evaluation of urban public transport performance and their relative contributions to overall destination satisfaction. Wu Hongyang et al. [3] applied econometric methods and built an urban traffic satisfaction evaluation model based on the customer satisfaction theory of social and experimental psychology and took Chengdu city as an example to test the model. Xiao Yumin [4] analyzed the three main factors affecting traffic satisfaction, such as air and noise pollution, useless loss of energy and road traffic conditions and established a mathematical model that can truly and effectively reflect the residents' satisfaction with traffic conditions. Fenglong Wang et al. [5] discussed whether and how the relocation of residence leads to changes in travel satisfaction and obtained that relocation of residence, improvement of neighborhood environment, more accessible facilities, better physical design, higher security and more interaction between neighbors contribute to improving travel satisfaction. A total of 1977 (in the quantitative section) and 19 (in the qualitative section) employees who have experienced an involuntary relocation of their workplace were examined vis-à-vis their travel-related values and attitudes, corresponding choices and satisfaction with a retrospective mixed-method approach by Zahra Zarabi et al. [6] The results showed that the relocation of the workplace was associated with increased public transit use and travel satisfaction and individuals do not necessarily use the most positively valued travel mode due to lack of accessibility and competences, but also due to having preferences for other travel-related elements such as travel route. Roberto F. Abenoza et al. [7] analyzed data on retrospective evaluations of entire multimodal trip experiences and satisfaction with individual trip legs. They formulated and described alternative aggregation rules and underpinned them in both theory and previous empirical findings. They came to the conclusion that, for a large number of multimodal trip configurations, normative rules can better reproduce overall travel satisfaction than heuristic rules. Other scholars have studied the residents' satisfaction with different modes of transportation: Ji Jue et al. [8] took public transportation in the eighth district of Beijing City as an example—and through the index of “public transportation accessibility”—linked the index of urban physical space structure with residents' satisfaction with public transportation and established an evaluation system of urban space structure with satisfaction as the target. Based on the basic feelings of urban road users, Sun Qian et al. [9] used an analytic hierarchy process and BP neural network to construct a set of urban road traffic satisfaction evaluation systems, to find out existing problems in the urban road traffic system and find out effective solutions. Wang Rong et al. [10] built an SEM-based satisfaction evaluation model for bus-transfer preferential policies and took Suzhou-bus transfer preferential policies as an example to verify the rationality of the model. Zhu Tong et al. [11] used the SEM to establish the quantitative relationship between various factors of the urban road environment and satisfaction of urban bicycle travelers and finally obtained the urban road bicycle-traveler satisfaction model after model testing and modification. Gao Hanying [12] combined the current situation of the Beijing subway and customer satisfaction theory, and proposed the influencing factors and evaluation indices of rail transit satisfaction. Jonas De Vos et al. [13] focused on the relation between mode choice and travel satisfaction for leisure trips (with travel-related attitudes and the built environment as explanatory variables) of study participants in urban and suburban neighborhoods in the city of Ghent, Belgium. It was shown that the built environment and travel-related attitudes—both important explanatory variables of travel mode choice—and mode choice itself affect travel satisfaction. Jesper Bláfoss Ingvarðson et al. [14] enhanced the framework for representing travel mode choice by incorporating the model of human needs as the missing link between mode choice and travel satisfaction. By developing and analyzing a large-scale survey from the Greater Copenhagen Area in Denmark, they empirically proved that commuting mode choice relates to travel satisfaction by answering functional, relatedness and growth needs. Hanne Tiikkaja et al. [15] based on the living environment, satisfaction with different transportation modes and the use of transportation modes, analyzed the satisfied-type, relatively satisfied-type and dissatisfied-type of traveler.

It can be seen that most of the current studies are based on the commonly used traditional models, and the number of selected indicators is small and relatively macro. These studies analyze problems

from the perspective of the objective setting of the environment and facilities, without reflecting the actual safety problems and subjective feelings encountered by urban residents during their travels and lack of analysis of potential safety hazards. Moreover, some studies put forward suggestions for optimizations, but do not evaluate the effect of these suggestions.

The nonaggregate model is often used in the study of residents' travel behavior, mainly including the multiple logit model, nested logit (NL) model, paired combination logit model, mixed logit model, etc. [16]. Moreover, improved models of the NL model and the probit model are also adopted. Shuhong Ma et al. [17] used a factor analysis method to study the significant factors influencing the bicycle riding characteristics of college students, and a two-layer NL model combining riding frequency and travel mode was established. The results suggested that environmental factors had a significant influence on the choice of travel mode and travel frequency and that the improvement of bicycle service level could increase the transition from walking to riding. Eran Ben-Elia et al. [18] established a hybrid logit specification discrete selection model to study the influence of information and experience on drivers' path selection behavior based on considering the panel effect. Yang Liya et al. [19] constructed a two-layer NL model, in which the characteristics of travelers, travel characteristics, and service level of travel mode were selected as the utility variables, and they, respectively took departure time and travel modes as the lower layer of the model to analyze residents' travel choice behavior. Vo Van Can [20] established several Probit models to study the travel choice behavior of tourists in Nha Trang, Vietnam. Jiang Wei et al. [21] took dynamic factors as independent variables and built a multinomial logit (MNL) Model to analyze the impact of these factors on residents' car rental choice behavior. Ransford A. Acheampong [22] used the Logistic regression model to analyze the influence of the type of land used by commuters in African cities on their attendance patterns. These models can also be used in studies of correlations with significant interactions: Natalia Casado-Sanz et al. [23] used a multinomial logit (MNL) model to find the most important factors involved in driver injury severity and the statistical analysis reveals that factors such as lateral crosstown roads, low traffic volumes, higher percentages of heavy vehicles, wider lanes, the non-existence of road markings, and finally, infractions, increase the severity of the drivers' injuries. Qingyou Yan et al. [24] used SEM (structural equation modeling) and MNL (multinomial logit model) models to analyze key factors affecting consumers' purchase intention and actual purchasing behavior and some reasonable suggestions are proposed for the government and EV (electric vehicles) enterprise service providers to increase electric vehicle diffusion. Yibin Ao et al. [25] investigated the relationship between the rural built environment and rural household vehicle ownership in China through a multinomial logit (MNL) model.

Most of these studies are only of high reference value when analyzing the current situation and have the problems of poor prediction accuracy and practicability. Therefore, they cannot be used to evaluate the expected effect after the implementation of optimized policies. As machine learning is gradually applied to urban traffic problems such as traffic flow prediction and travel behavior analysis, scholars at home and abroad have found that they have a better ability to classify data through research. Li Xiugang et al. [26] applied the SVM model to vehicle collision prediction and proved that the model was faster and more effective than the traditional binomial prediction model. Xing Wang et al. [27] compared the confidence band estimators of the SVM model and the Logistic regression model and found that the classification accuracy of SVM was higher than that of the Logistic regression model. Wang Shengyou et al. [28] constructed an NL model and an SVM model based on the residents' travel data within the scope, analyzed and predicted the residents' travel mode selection behavior before and after the implementation of the optimization and improvement measures, and verified the effectiveness of the model and the optimization effect of the improvement measures. Yan Jialin et al. [29] applied LSTM to urban road-traffic speed prediction. Cao Yu et al. [30] used LSTM to predict short-term traffic flow on urban roads, which reduced the error of other methods. These studies prove that the prediction results of the neural network model are more accurate than the traditional regression model.

3. Research Design and Methods

In this paper, the impacts of personal attributes, family attributes and various safety hazards on residents' travel safety and satisfaction are analyzed based on actual survey results using an MNL model. Then significant factors are taken as factors affecting satisfaction evaluation and a support vector machine (SVM) model is used to simulate subjective satisfaction evaluation of residents. After the travel optimization measures are proposed, travel satisfaction is measured by using the training model to evaluate the effectiveness of the measures.

3.1. The MNL Model

Regression analysis is often used to analyze the correlation between explanatory variables and explained variables. When explanatory variables are not completely numeric and explained variables are of multitype, the multinomial logit model (MNL) is adopted. In this paper, resident travel satisfaction is divided into five levels, namely "very satisfied", "relatively satisfied", "neutral", "relatively dissatisfied" and "very dissatisfied". Using the stochastic utility theory, the basic utility function can be expressed as follows:

$$U_{aj} = V_{aj} + \varepsilon_{aj} \quad (1)$$

In the above equation, U_{aj} represents the utility function of traveler A's selection of the j th satisfaction level. V_{aj} represents the observable influencing factors, namely the certain term. ε_{aj} represents the unobtainable factors, namely the random term. Different models can be deduced when different distribution assumptions are taken for random terms. According to the random utility maximization theory, the probability that traveler A chooses the j th satisfaction level can be expressed as P_{aj} :

$$P_{aj} = P(U_{aj} > \max_{j \neq l} U_{aj}, j \neq l, l = 1, 2, 3, 4, 5) \quad (2)$$

In this paper, the explained variable is the satisfaction level, and there are five choices. To study the factors affecting the resident travel satisfaction, the MNL model is constructed. The selected explanatory variables include the following aspects: individual attribute, family attribute and safety hazard, with a total of 13 variables. Three assumptions need to be made before the model can be built: (1) The traveler always chooses the most effective of the various satisfaction levels first; (2) The definite term is independent of the random term; (3) The random items are independently and identically distributed and all follow the Gumbel distribution.

Then the probability that traveler A chooses the j th satisfaction level can be expressed as:

$$P_{aj} = \frac{\exp(V_{aj})}{\sum_{j=1}^5 \exp(V_{aj})} \quad (3)$$

V_{aj} is considered to be a linear combination of various influencing factors, and its expression is:

$$V_{aj} = \varepsilon_0 + \varepsilon_1 X_{aj1} + \varepsilon_2 X_{aj2} + \cdots + \varepsilon_{13} X_{aj13} \quad (4)$$

In the above equation, ε_0 is a constant term, $X_{aj1} \sim \varepsilon_{13} X_{aj13}$ are the 13 variables that influence the way travelers choose to travel. $\varepsilon_1 \sim \varepsilon_{13}$ are the undetermined coefficients of each variable. Therefore, the probability that traveler A chooses the j th satisfaction level is:

$$P_{aj} = \frac{\exp(V_{aj})}{\sum_{j=1}^5 \exp(V_{aj})} = \frac{\exp(\varepsilon_0 + \varepsilon_1 X_{aj1} + \varepsilon_2 X_{aj2} + \cdots + \varepsilon_{13} X_{aj13})}{\sum_{j=1}^5 \exp(\varepsilon_0 + \varepsilon_1 X_{aj1} + \varepsilon_2 X_{aj2} + \cdots + \varepsilon_{13} X_{aj13})} \quad (5)$$

The satisfaction level with the highest probability of being selected in the model results is considered as the final satisfaction level.

3.2. The Support Vector Machine Model

The support vector machine model (SVM) [31] uses a method of transforming a nonlinear separable problem into a linearly separable problem by mapping the sample space to a higher-dimensional feature space. It uses sample data as the basis and trains the data to find the rules, then uses the correlation between data to predict unknown results. Linear classification problems are generally solved by adding a hyperplane method and nonlinear classification problems need to be solved by adding a kernel function to assist sample data mapping.

There are individual differences among urban residents, which are reflected in the age, income and number of cars owned by individuals. However, there are certain connections between individuals, which are manifested in the similarity of certain characteristic attributes. Residents' travel satisfaction is affected by individual attributes, family attributes and potential safety hazards. By analyzing the travel satisfaction of samples with different characteristics, using the support vector machine to fit the sample data, the evaluation model of resident travel satisfaction based on SVM can be obtained. The modeling process is shown in Figure 1.

Figure 1. Modeling process.

According to the significant influencing factors obtained in the previous section, let the 13 influencing factors in the input sample be $\{x_i^1, x_i^2, x_i^3, \dots, x_i^{13}\}$. The satisfaction evaluation level is $y_i = f(x_i)$. Then the sample data set is $\{x_i^1, x_i^2, x_i^3, \dots, x_i^{13}, y_i\}$. The data sample is divided into two parts. One part is used as the training set, and the other part is used as the verification set to train the prediction accuracy of the model. In actual operation, it is divided into a training set and sample set according to 8:2.

In the training set, for all the x_i ,

$$f(x) = \omega^T \varphi(x) + b \quad (6)$$

Then the objective function can finally be expressed as:

$$\begin{aligned} & \min \frac{1}{2} \|\omega\|^2 \\ & \text{s.t. } y(\omega^T \varphi(x) + b) \geq 1 \end{aligned} \quad (7)$$

The dual function is:

$$\begin{aligned} \max \sum_i a_i - \frac{1}{2} \sum_i \sum_j a_i a_j y_i y_j \varphi(x_i)^T \varphi(x_j) \\ \text{s.t.} \begin{cases} \sum_i a_i y_i = 0 \\ a_i \geq 0 \end{cases} \end{aligned} \quad (8)$$

To solve the dual problem, let the kernel function be $K(x_i, x_j) = \langle \varphi(x_i), \varphi(x_j) \rangle = \varphi(x_i)^T \varphi(x_j)$, then the above equation can be expressed as:

$$\begin{aligned} \max \sum_i a_i - \frac{1}{2} \sum_i \sum_j a_i a_j y_i y_j K(x_i, x_j) \\ \text{s.t.} \begin{cases} \sum_i a_i y_i = 0 \\ a_i \geq 0 \end{cases} \end{aligned} \quad (9)$$

The solution can be obtained as follows:

$$f(x) = \omega^T \varphi(x) + b = \sum_i a_i y_i K(x_i, x_j) + b \quad (10)$$

According to different sample data and requirements, kernel functions of SVM are mainly divided into the following four types:

(1) Linear kernel function:

$$K(x_i, x_j) = (x_i^T x_j)^1 \quad (11)$$

(2) Polynomial kernel function:

$$K(x_i, x_j) = (x_i^T x_j)^d \quad (12)$$

In the above equation, d is the degree of the polynomial. When $d = 1$, it degenerates into a linear kernel.

(3) Radial basis kernel function:

$$K(x_i, x_j) = \exp\left(-r \frac{\|x_i - x_j\|^2}{\sigma^2}\right) (\sigma > 0) \quad (13)$$

(4) Sigmoid kernel function:

$$K(x_i, x_j) = \tanh(\lambda x_i^T x_j + \theta) (\lambda, \theta > 0) \quad (14)$$

After the kernel function is introduced, the relaxation variable $\gamma \geq 0$ and the penalty factor $C > 0$ need to be introduced to process the sample data that is far from the normal position. The larger the value of C is, the greater the penalty for classification error is. Then the objective function is modified as:

$$\begin{aligned} \min \frac{1}{2} \|\omega\|^2 + C \sum_i \gamma_i \\ \text{s.t.} y_i (\omega^T \varphi(x_i) + b) \geq 1 - \gamma_i \end{aligned} \quad (15)$$

After writing the Lagrange function, it is transformed into a dual problem to find the optimal parameter model.

3.3. The Prediction Model

In the resident travel satisfaction evaluation model, the characteristic attributes with significant influence are used as the test sample data x_i to input the SVM resident travel satisfaction evaluation model and y_i is output as the results of resident travel satisfaction after the implementation of optimization measures. Therefore, the prediction flow chart is shown in Figure 2.

Figure 2. Travel satisfaction prediction.

4. Investigation and Analysis

A survey was conducted on the travel data of residents in Futian District, Shenzhen in January 2019. The survey area is shown in Figure 3. Futian District has a total population of about 370,000. The sample was randomly selected and covered all the residential districts. The sample size was proportional to the population of each district. This survey adopted the form of paper questionnaire. The respondents included Futian Street, Shatou Street and Fubao Street in Futian District of Shenzhen. Three parts were designed, with a total of 28 questions, which were basic information of residents, security risks in Futian District and daily travel information, respectively. A total of 5000 questionnaires were distributed, including 3000 from Futian Street, 1000 from Shatou Street and 1000 from Fubao Street. A total of 4674 valid questionnaires were recovered, with an effective recovery rate of 93.48%. Through preliminary screening, 3141 valid questionnaires were obtained after removing incomplete/incorrect questionnaires. After sorting and summarizing the collected data, the distribution of the eight basic information such as gender and age of the surveyed residents is shown in Table 1.

Figure 3. Survey area.

Table 1. Residents travel information characteristics distribution.

Basic Information	Classification	Sample Size	Percentage (%)
Sex	Male	1781	56.70%
	Female	1360	43.30%
Age (years)	10–18	107	3.40%
	18–25	408	13.00%
	25–35	1039	33.10%
	35–45	986	31.40%
	45+	601	19.10%
Job	Student	172	5.50%
	Full-time employee	1426	45.40%
	Temporary employee	493	15.70%
	Freelancer	873	27.80%
	Retired people	177	5.60%
Education	Junior high school and below	564	18.00%
	Secondary and senior secondary school	1221	38.90%
	Junior college and undergraduate	1071	34.10%
	Postgraduate and above	285	9.10%
Income (Yuan)	≤50,000	474	15.10%
	50,000–100,000	1307	41.60%
	100,000–200,000	868	27.60%
	>200,000	492	15.70%
Car	0	1432	45.60%
	1	1577	50.20%
	2	132	4.20%
Living area	Futian District	2301	73.30%
	Luohu District	475	15.10%
	Nanshan District	217	6.90%
	Yantian District	66	2.10%
	Baoan District	45	1.40%
	Longgang District and other areas	37	1.20%
People	1	598	19.00%
	2	1367	43.50%
	3	230	7.30%
	4	456	14.50%
	5	390	12.40%
	6	100	3.20%

It can be seen from Table 1 that the proportion of male respondents was 56.7%—slightly higher than that of female respondents, which was 43.3%. Most of the participants were between 25 and 45 years old, accounting for 64.5%. This means that young and middle-aged travelers were more likely to take part in the survey. The proportion of full-time travelers was 45.4% (the highest). The education level of the respondents was mainly focused on secondary and higher education, so the data obtained from the survey were representative to some extent. Among these travelers, the annual household income of “50,000–100,000” was the highest, accounting for 41.6%, followed by “100,000–200,000”, accounting for 27.6%. The data distribution was relatively reasonable. A total of 45.6% of the respondents did not own a car, 50.2% owned one car, 4.2% owned two cars. This was within the normal range. Of the travelers, 73.30% lived in the Futian District, while other travelers temporarily lived in Futian District for some reason, so they participated in the survey. It can be seen from the above data that the structure of each characteristic value of the respondents was evenly distributed and sufficiently representative. Moreover, the above characteristics were analyzed as factors affecting resident travel satisfaction. There were five levels of resident travel satisfaction evaluation, namely “very satisfied”, “relatively satisfied”, “neutral”, “relatively dissatisfied” and “very dissatisfied”. According to the

survey, 628 cases were “very satisfied”, 1314 cases were “relatively satisfied”, 824 cases were “neutral”, 239 cases were “relatively dissatisfied” and 136 cases were “very dissatisfied”. The satisfaction rate (both very satisfied and relatively satisfied) was only 61.8%. The proportion distribution of each grade is shown in Figure 4.

Figure 4. Travel satisfaction evaluation grade distribution in Futian District, Shenzhen.

5. Experiment and Verification

5.1. Analysis of Influencing Factors

For better fitting, the 13 selected variables were redefined as shown in Table 2.

The five satisfaction levels were defined as 1—very satisfied, 2—relatively satisfied, 3—neutral, 4—relatively dissatisfied and 5—very dissatisfied. The MNL model was calibrated with the software SPSS.24. Thirteen influencing factors were added to the factor column, “satisfaction level” was added to the dependent variable column, variable attributes were adjusted, reference categories were set. The system defaults to the first category of each variable as a reference. After parameter estimation, the model fitting effect is shown in Table 3.

The significance was less than 0.05, indicating that the final model had statistical significance and the model was established. The pseudo-R-squared value should be between 0 and 1 and the bigger the better. However, if it is too big, there is a possibility of overfitting. The three pseudo-R-squared values produced by the model were between 0.3 and 0.7, and the model had a good fitting degree, which can make reasonable fitting for different data.

Analyzing the parameter estimation results, one can reach the following conclusions:

- (1) The following attributes of residents all had a certain impact on resident travel satisfaction: age, occupation, education level, number of cars, income, living area, etc. Traffic participants, vehicles, roads, traffic safety management, traffic infrastructure, etc. safety hazards had a significant impact on resident travel satisfaction. Among them, the safety hazards of traffic participants, vehicles and roads were more likely to make residents dissatisfied with the travel experience;
- (2) Compared with other factors, the safety risks caused by irregular bus and bicycle driving were more likely to made residents very dissatisfied with their travel experience;
- (3) Safety hazards such as pedestrians crossing the street illegally, irregular driving of private cars, illegal driving of delivery vehicles, and illegal driving of non-motor vehicles reduced the actual satisfaction level of residents who were otherwise very satisfied with their travel experience.

Table 2. Variable definitions.

Category	Variable	Variable Definition
Individual attributes	Sex	1—Female; 2—Male
	Age (years)	1—10–17; 2—18–24; 3—25–34; 4—35–44; 5—45–100
	Job	1—Student; 2—Full-time employee; 3—Temporary employee; 4—Freelancer; 5—Retiree; 6—Other
	Education	1—Junior high school or below; 2—Technical secondary school and high school; 3—College and bachelor; 4—Postgraduate or above
Family attributes	Income (Yuan)	1—0–49,999; 2—50,000–99,999; 3—100,000–199,999; 4—200,000–499,999; 5—more than 500,000
	Number of cars	Continuous variable, unit—vehicle
	Family members	Continuous variable
	Area	1—Futian District; 2—Luohu District; 3—Nanshan District; 4—Yantian District; 5—Baoan District; 6—Longgang District and other areas
Safe risk	Traffic participant	1—Irregular driving of taxis/ ride-hailing; 2—Illegal pedestrian crossing; 3—Irregular driving of private cars; 4—Irregular driving of delivery vehicles; 5—Irregular driving of non-motor vehicles; 6—Others
	Vehicle	1—Private cars; 2—Taxis/ride-hailing; 3—Buses; 4—Bicycles; 5—Delivery vehicles; 6—Others
	Road	1—Unreasonable intersection design; 2—Unreasonable section design; 3—Traffic organization around large passenger flow distribution centers; 4—Others
	Traffic safety management	1—Lack of traffic management; 2—Lack of driving codes; 3—Unreasonable design of traffic lights; 4—Irregular traffic signs and marking; 5—Random parking of shared bicycles; 6—Irregular parking management; 7—Others
	Key safety hazard	1—Traffic participant; 2—Vehicle; 3—Road; 4—Traffic safety management; 5—Others
	Unsafe area	1—Futian station; 2—Shopping park; 3—Binhe-Huanggang Interchange; 4—Fuhua Interchange; 5—Shennan-Huanggang Interchange; 6—Yitian Road; 7—Gangxia Road; 8—Fumin Road; 9—Others
	Transportation infrastructure	1—Overpass; 2—Crossing light; 3—Pedestrian crossing; 4—Nonmotorized lane; 5—Public parking lot; 6—Taxi stop; 7—Parking lot of shared bicycle; 8—Isolation facility; 9—traffic signs and marking; 10—Others

Table 3. Effect of multinomial logit (MNL) model fitting.

Model Fitting Information						
Model	Model Fitting Conditions		Likelihood Ratio		Pseudo R-Squared	
Null Hypothesis General	−2 Log Likelihood	chi-squared	df	Significance	Cox and Snell	0.598
	8581.621				Nagelkerke	0.639
	5720.484	2861.137	248	0.000	McFadden	0.333

5.2. The Model Fitting

In this paper, the radial basis kernel function with a smaller deviation can be selected to achieve higher prediction accuracy. The value range of parameter C was set to 0.01–1000, the value range of γ is set to 0.01–1000. After parameter optimization, the classification accuracy was the highest when C was set as 10 and γ as 1. Meanwhile, a fitting accuracy curve was drawn as shown in Figure 5. It can be seen that the fitting accuracy is about 87.76%.

Figure 5. Curve of fitting accuracy.

5.3. Optimization Measures and Effect Prediction

The formulation of relevant measures to improve the safety level of significant factors can improve the travel environment and ensure travel safety. At the same time, it can improve resident travel satisfaction. In the previous section, an SVM model was established to measure the travel satisfaction of residents by analyzing the travel satisfaction of different feature samples. This model can be used to measure the travel satisfaction of other samples with similar characteristics, and then the travel satisfaction rate of residents in different environments can be obtained.

Based on the previous analysis, to improve the convenience of travel, promote the implementation of “green travel” and strengthen the connection between various modes of transportation, the following two travel optimization measures are proposed from the perspective of improving the overall travel efficiency and traffic resource allocation:

Option 1: Most roads in Shenzhen do not have non-motorized vehicle lanes, which will hinder residents from choosing non-motorized vehicles to travel. Residents driving non-motorized vehicles on motorized lanes will have great safety risks. Therefore, it is recommended to add non-motorized vehicle lanes. Planning the structure of the non-motor vehicle road network can alleviate the “last mile” problem. Meanwhile, it can enhance the convenience of residents’ travel and resident travel satisfaction;

Option 2: The distance between some bus stations and intersections is less than 50 m, and many buses queue at the intersection, which does not meet the requirements of the design standards. In addition to causing multiple buses to queue and causing traffic congestion, it is also easy to induce

traffic accidents and bring traffic safety hazards. Therefore, it is recommended to appropriately move the location of the bus station and improve the safety facilities of the bus station, such as adding protective fences and widening the passenger waiting area. These measures can not only reduce congestion, but also encourage residents to use public transportation to travel.

Option 1 assumes that 50% of residents who think that “non-motorized vehicle hazards” have a significant impact on their travel satisfaction will no longer be affected by this and choose “other hazards” instead. Option 2 assumes that 50% of residents who think that “bus hazard” has a significant impact on their travel satisfaction will no longer be affected by this. Instead, they choose “other hidden hazards”. The SVM resident travel satisfaction evaluation model is used to predict travel satisfaction after the optimization measures are implemented. The results are shown in Table 4.

Table 4. Comparison of different options.

Satisfaction Level	Sample (Quantity/Proportion)	Option 1	Option 2	Comprehensive Effect
Very satisfied	628 (20.0%)	571 (18.18%)	497 (15.82%)	473 (15.06%)
Relatively satisfied	1314 (41.8%)	1558 (49.60%)	1734 (55.21%)	1910 (60.81%)
Neutral	824 (26.2%)	728 (23.18%)	628 (19.99%)	564 (17.96%)
Relatively dissatisfied	239 (7.6%)	158 (5.03%)	213 (6.78%)	131 (4.17%)
Very dissatisfied	136 (4.3%)	126 (4.01%)	69 (2.20%)	63 (2.01%)

It can be seen from Table 4 that under the assumption of option 1, the number of residents who were predicted to be satisfied (including very satisfied and relatively satisfied) increased by 187 cases compared with the original sample, and the number of dissatisfied (including relatively dissatisfied and very dissatisfied) decreased by 91 cases compared with the original sample. Under the assumption of option 2, the number of residents who were predicted to be satisfied (including very satisfied and relatively satisfied) increased by 289 cases than the original sample, and the number of dissatisfied (including relatively dissatisfied and very dissatisfied) decreased by 90 cases than the original sample. Under the assumptions of integrated option 1 and option 2, the number of residents who were predicted to be satisfied (including very satisfied and relatively satisfied) increased by 441 cases, and the number of dissatisfied (including relatively dissatisfied and very dissatisfied) decreased by 181 cases compared with the original sample. The rate of change of each satisfaction level after the implementation of each option is shown in Figure 6.

Figure 6. Changes in the percentage of satisfaction levels under various options.

It can be seen from Figure 6 that after the implementation of option 1, the travel satisfaction rate of residents (including very satisfied and relatively satisfied, the same below) increased by 5.92%, after the implementation of option 2, the travel satisfaction rate of residents increased by 9.23%. After the implementation of the comprehensive option, the travel satisfaction rate has increased by 14.07%.

Under the three hypothetical situations, the proportion of residents who choose “relatively satisfied” increased, but the proportion of residents who choose “very satisfied” decreased. The reason for the analysis may be when a specific safety hazard is unilaterally improved, the linkage influence caused by other aspects in the optimization process is not fully considered, resulting in the decrease of travel satisfaction of some residents who are significantly affected by other aspects of the hazard. Therefore, the proportion of residents who choose “very satisfied” decreased. However, optimization measures can promote the improvement of the overall travel experience evaluation, so the travel satisfaction rate is significantly improved. Under the three different assumptions, the proportion of residents dissatisfied with their travel experience decreases. Therefore, it is believed that the above travel optimization measures can improve residents’ travel environment and enhance resident travel satisfaction. These measures play a significant role in improving the travel structure and promoting the development of “green traffic”.

5.4. Discussion

In the experiment, significant factors affecting resident travel satisfaction were obtained, which were used as explanatory variables to fit the evaluation model of resident travel satisfaction. Moreover, corresponding policy optimization suggestions were proposed based on the results. Finally, the effect of policy implementation was predicted, which would provide an effective reference for Futian District to make the following traffic strategies. Previous studies focused on finding significant influencing factors, building evaluation models and empirical tests. They occasionally put forward improvement measures but did not predict the effect of measures after implementation. In addition, few scholars have used SVM model with high fitting accuracy to predict travel satisfaction, which is an innovation of this paper.

6. Conclusions

In this paper, first, the MNL model was constructed to study the significant factors affecting urban resident travel satisfaction. Stochastic utility maximization theory was applied to estimate the model parameters. The model was tested and analyzed with the help of SPSS software. Then, the factors that had no significant influence on the resident travel satisfaction were removed from the sample data. The current situation sample data were divided into a training set and a test set. The support vector machine was used to fit the sample data to obtain a resident travel satisfaction evaluation model and input the test set to obtain a model-fitting accuracy of about 87.76%. Finally, two kinds of travel optimization measures were proposed from the perspective of improving residents’ travel safety. To evaluate the effect of policy implementation, the SVM resident travel satisfaction evaluation model was used to predict resident travel satisfaction under the optimized measures. The research draws the following conclusions:

1. The safety hazards impacted resident travel satisfaction in the following aspects: age, job, education, number of cars, income, residential area and other attributes, as well as the safety risks of traffic participants, vehicles, roads, traffic safety management, traffic infrastructure and other aspects all, had an impact on the resident travel satisfaction;
2. The more serious the safety hazards of traffic participants, vehicles and roads were, the more dissatisfied the residents were with the travel experience;
3. The potential safety hazards caused by the irregular driving of buses and bicycles made residents dissatisfied with their travel experience. Potential safety hazards, such as pedestrians crossing the street illegally, irregular driving of private cars, express vehicles and non-motor vehicles, greatly reduced resident travel satisfaction level.
4. The addition of non-motorized lanes and the reasonable location of bus stations—as well as the improvement of their safety facilities—raised the satisfaction rate of residents’ travel by 14.07%.

The conclusion of this study may not only improve the safety and satisfaction of residents and promote the development of “green travel” and sustainable transport, but also provide a reference for relevant departments making transport policies.

In future research, experienced people should be arranged to guide respondents to complete the questionnaire to ensure the quality of the returned results. Moreover, when considering the influencing factors, a more detailed and comprehensive classification should be made to reflect the significant factors that affect the resident travel satisfaction more accurately. At the same time, a practical investigation will also be carried out on the effect of optimization measures after implementation to verify the predicted effect.

Author Contributions: Z.X. analyzed the current data, used the MNL model to find the significant influencing factors, then proposed the optimization measures and analyzed the optimized effect; C.S. provided an overall framework of the present work and optimized the overall article; S.W. designed portions of parameters in the proposed model and tested the model; C.D. provided status data and made modifications to the article. All authors have read and agreed to the published version of the manuscript.

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