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Road Safety Risk Identification Driven by Abnormal Driving Behavior Data

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Abstract: With the development of vehicle network technology, transportation companies have generated GPS-based driver behavior data for operating vehicles, providing potential for research on driver behavior and road safety risk perception. Research on road safety risk perception at the present stage generally involves fuzziness and subjectivity, the degree of risk is difficult to quantify, and big data-based road safety risk perception has not yet been used practically. To address this problem, this paper proposes a method of quantifying the degree of road safety risk based on the hierarchical analysis method and fuzzy comprehensive evaluation method under the drive of abnormal driving behavior data, constructs a scientific and reasonable urban road safety risk identification comprehensive evaluation model, and explores important factors affecting road safety. The research results have a certain reference effect for traffic management departments to accurately locate dangerous sections in the urban road network.

Keywords: Internet of Vehicles, Driver behavior data, Traffic safety, Analytic hierarchy process, Fuzzy comprehensive evaluation method.

1. Introduction

In the relevant research of road traffic safety, the cause of accidents has always been the focus of scholars. In an earlier authoritative study, scholars calculated that the proportion of road traffic accidents caused by human factors was about 92.6% [1]; In recent years, scholars have further studied the relationship between human factors and traffic accidents, and found that more than 95% of accidents are caused by drivers' failure to take emergency measures, or by abnormal driving behaviors such as overloading and speeding [2]. Therefore, the research on abnormal driving behavior has become the focus of the research on the causes of accidents, and the monitoring and analysis of driver behavior is the basis of driver management.

At present, the actual application of driving behavior data is mostly to identify the risk of drivers and conduct passive control afterwards. With the support of Internet data, how to realize the identification of road safety risks is another direction of driving behavior data application. With the development of the Internet of Vehicles technology in the field of transportation [3], driving behavior data with large sample size, fast transmission speed and strong real-time are produced. Based on the vehicle track, operation status and early warning information collected by the freight vehicle Internet of Vehicles terminal, Zhang Jingang et al. [4] studied the spatiotemporal distribution characteristics of the freight vehicle driving early warning events such as fatigue driving early warning, overspeed driving early warning and collision early warning during the driving process, identified the hot sections producing early warning and revealed its main influencing factors; Ye Yuntao [5] takes traffic conflict as the reflection index of expressway operation risk level, classifies expressway operation risk level through K-means clustering method, and establishes expressway operation risk analysis model with multiple logistic model to study the influencing factors of expressway operation risk. Relevant research shows that the Internet of Vehicles data has practical application value for road link risk assessment.

The abnormal driving behavior data used in this paper is, to a certain extent, the collection of all the above evaluation indicators on the driver's behavior, and the data reflection of the driver's behavior habits and the safety risks existing on the road. The data indicators of such natural driving data cover a wide range of areas, are real-time, and are difficult to obtain. Comprehensive evaluation of road safety based on abnormal driving behavior data is a new way to study road safety risks.

2. Data Introduction

Based on the GPS data generated by the online car rental enterprises, the access is to obtain the driving behavior data that can reflect the driver's behavior through the online car rental driver's mobile phone location, including the abnormal driving behavior rate on each road section of overspeed, rapid acceleration, rapid deceleration, rapid lane change and sharp turn. As shown in Tab 1.

Table 1. Segmentation extraction result table of abnormal driving behavior rate (part)

link_id	link_ coor_arr	Traffic volume	Abnormal driving behavior rate（%）				
			Over speed	rapidacc	rapiddece	sharp	sharpchan
14900778	POLYGON ((116.90976 36.65132……))	176623	0.191	0.199	0.039	0.015	0.007
14900779	POLYGON ((116.90930 36.65130……))	163021	0.222	0.077	0.021	0.007	0.006
35847751	POLYGON ((116.91187 36.65128……))	169685	0.098	0.050	0.029	0.008	0.004
35847752	POLYGON ((116.91090 36.65130……))	172287	0.099	0.045	0.025	0.002	0.006
…	…	…	…	…	…	…	…

3. Road Safety Risk Assessment Index System

In the relevant research of road safety risk, the selection of evaluation indicators is the first task to establish a comprehensive evaluation model. From the three aspects of people, vehicles and roads involved in traffic, scholars select scientific and reasonable evaluation indicators from many factors affecting urban road traffic safety. Liu Yun et al. [6] screened out the evaluation indicators that have a great impact on urban road traffic safety. The main indicators include traffic composition, traffic volume, traffic safety facilities, geometric alignment, pavement quality, cross section composition, and intersection to evaluate road traffic safety. By analyzing the research results of the existing urban road traffic risk assessment indicator system, it is found that the current research has problems such as difficulty in quantifying indicators, incomplete coverage of indicators, and the corresponding indicators are difficult to obtain, and the system is too complex. This paper selects the behavior rate of five kinds of abnormal driving behaviors, such as overspeed, rapid acceleration, rapid deceleration, sharp lane change, and sharp turn, on each section of the road as the evaluation index of road safety risk, constructs a road safety risk evaluation index system, comprehensively considers subjective and objective factors, and uses the analytic hierarchy process to determine the index weight of each abnormal driving behavior.

AHP weight assignment

(1) Construct hierarchy model

The decision-making problem is mainly divided into three parts: target level, criterion level and index level. Put the target of the problem to be solved at the target level. In order to achieve the overall goal, set some general relevant criteria as the criteria level, and refine each criterion to put forward the indicator level. The specific structure is shown in Figure 1.

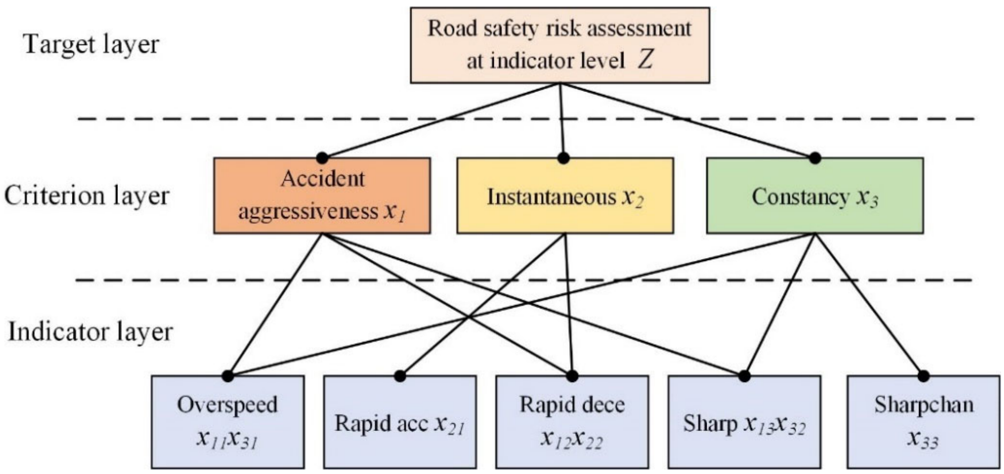

Figure 1. Road safety risk assessment index system

(2) Construct importance judgment matrix

The judgment matrix of each level is constructed according to the importance of each factor compared with other factors. According to the degree of influence of the same level on the indicators of the next level, the indicators of the same level are compared quantitatively, and the evaluation results form the judgment matrix A.

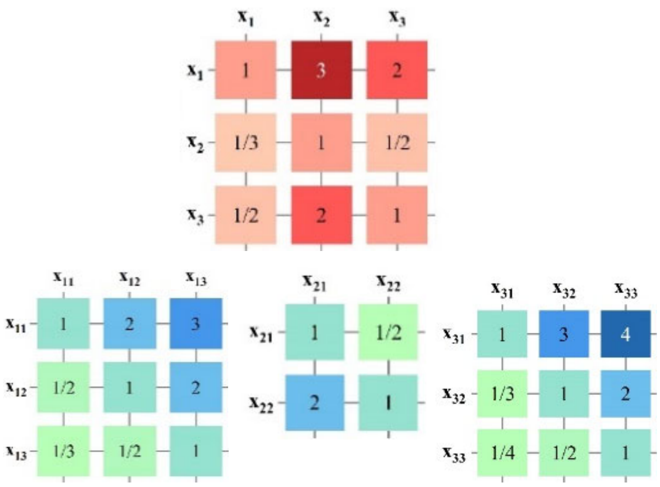

Figure 2. AHP judgment matrix

(3) Consistency inspection

In order to prevent the scoring difference between the subjects from being too large to ensure the consistency of the scoring of each indicator, it is necessary to test the consistency of all scoring to verify whether the judgment matrix is approved. This part first calculates the weight vector.

1) Normalize each column of the judgment matrix to obtain the weight matrix $\overline{w} = \left(\overline{w_{ij}}\right)_{n\times n}$.

$$\overline{w_{ij}} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{1}$$

2) The matrix w is obtained by summing the rows and calculating the mean value.

$$w_i = \frac{1}{n}\sum_{j=1}^{n}\overline{w_{ij}} \tag{2}$$

3) Multiply judgment matrix A and matrix w to obtain matrix Y.

$$Y = A\times w = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}\begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{3}$$

4) Calculate the maximum characteristic root of judgment matrix A.

$$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{w_i} \tag{4}$$

Conduct consistency check again. Calculate the random consistency ratio (CR).

$$CR = \frac{CI}{RI} \tag{5}$$

Where RI is a random consistency parameter and CI is a consistency factor. CI calculation method is Formula 6, and RI value is shown in Table 2.

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{6}$$

Table 2. Random one-time parameter (RI) value table

Matrix order	1	2	3	4	5	6	7	8	9
RI	0	0	0.52	0.89	1.12	1.25	1.36	1.41	1.46

Based on the judgment matrix, the weight vector is calculated and the consistency is checked. The weight vector is calculated, and the weight of the criterion layer is $X = [0.5396, 0.1634, 0.2970]$, the maximum characteristic root is 3.0092, CR=0.009<0.1, which passes the consistency test. Similarly, the calculated weight of accident propensity behavior index layer is $X_1 = [0.5396, 0.2970, 0.1634]$, the maximum characteristic root=3.0092, CR=0.009<0.1, which passes the consistency test; The weight of instantaneous abnormal behavior index layer is $X_2 = [0.3333, 0.6667]$, the maximum characteristic root=2, CR=0<0.1, which passes the consistency test; The weight of the indicator layer of persistent abnormal behavior is $X_3 = [0.6251, 0.2384, 0.1365]$, the maximum characteristic root is 3.018, CR=0.01<0.1, and it passes the consistency test.

(4) Total hierarchical sorting

Complete the consistency test of the judgment matrix at each level, and calculate the index weight of the index layer factors for the total target Z by calculating the product of the index layer weight and the criterion layer weight, and then sort.

Table 3. Subjective weight assignment results of abnormal driving behavior indicators

Criterion / Indicator	Accident aggressiveness x_1 (0.5396)	Instantaneous x_2 (0.1634)	Constancy x_3 (0.2970)	weight
Overspeed x_{11}/x_{31}	0.5396	0	0.6251	0.4768
Rapid acc x_{21}	0	0.3333	0	0.0545
Rapid dece x_{12}/x_{22}	0.2970	0.6667	0	0.2692
Sharp x_{13}/x_{32}	0.1634	0	0.2384	0.1590
Sharpchan x_{33}	0	0	0.1365	0.0405

4. Road Safety Risk Assessment Model Based on Fce

Based on the weighted results of abnormal driving behavior indicators determined by AHP, this paper establishes a road safety risk evaluation model based on fuzzy comprehensive evaluation (FCE) to identify the road safety risk level.

4.1. FCE three-part determination

The three sets of the road safety risk assessment model based on the fuzzy comprehensive evaluation method include the factor set, the comment set and the weight set, which are the basic data sets for the fuzzy comprehensive evaluation algorithm.

(1) Construct the factor set of road safety risk assessment model $U = \{u_1, u_2, u_3, u_4, u_5\}$, which represents the overspeed ratio, rapid acceleration ratio, rapid deceleration ratio, rapid lane change ratio and sharp turn ratio.

(2) The evaluation set of road safety risk assessment model is constructed $V = \{v_1, v_2, v_3, v_4\}$, which represents safety, good, general and dangerous respectively. See Table 4 for the

corresponding value set of the evaluation set.

Table 4. Road safety risk assessment set and corresponding score setting

Comment Set	safe	good	general	dangerous
fraction	90	70	50	30

(3) The weight set of road safety risk assessment model is constructed $W = [w_1, w_2, w_3, w_4, w_5]$, which corresponds to the comprehensive weight determined by AHP-EW integrated weighting method, $W = [0.4768, 0.0545, 0.2692, 0.1590, 0.0405]$.

4.2. Membership degree and fuzzy comprehensive evaluation

The membership function is a group of functions used for fuzzy sets. This function can map the given index value to the specified range, evaluate the membership of the index to the hierarchical fuzzy subset from a single factor, and then establish the membership matrix R. In this paper, the trapezoidal distribution function with the widest applicability is selected as its membership function to construct the membership matrix. Taking the data of section 14900778 in Table 4.6 as an example, the calculation result of membership matrix is

$$R = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0.01 & 0.99 \\ 0 & 0.55 & 0.45 & 0 \\ 0 & 0.25 & 0.75 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

Carry out fuzzy operation of membership matrix

$$S = W \text{ z } R$$

$$= (0.4768, 0.0545, 0.2692, 0.1590, 0.0405) \text{ z } \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0.01 & 0.99 \\ 0 & 0.55 & 0.45 & 0 \\ 0 & 0.25 & 0.75 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$= [0, 0.2283, 0.7110, 0.0540]$$

Based on the principle of maximum subordination, the final risk grade of section 14900778 is evaluated as relatively dangerous. The comprehensive safety risk score of this section is 53.15 points using the risk grade score in Table 4.

5. Conclusion

Based on the data of abnormal driving behavior, this paper proposes a quantitative method of road safety risk degree based on analytic hierarchy process and fuzzy comprehensive evaluation method, establishes a road safety risk evaluation model, and realizes the safety risk identification of urban road network. First, the AHP is used to determine the weight of indicators, explore the key behavioral factors that affect road safety risk, and reveal the differences between indicators of abnormal driving behavior. According to the weight determination results of each index, based on the basic idea of fuzzy comprehensive evaluation method set, a scientific and reasonable urban road safety risk evaluation model is established, and a quantitative method of urban road risk degree is proposed. Finally, an example analysis of the road section with the number of 14900778 was completed, and the accuracy of the model was verified through the actual situation of the road section. Finally, the overall risk assessment and analysis of a city road network in Shandong Province was completed.

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