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Risk Assessment Model and Sensitivity Analysis of Ordinary Arterial Highways Based on RSR–CRITIC–LVSSM–EFAST

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Abstract: In this paper, in order to evaluate the traffic safety status of ordinary arterial highways, identify the sources of safety risks, and formulate safety development countermeasures for arterial highways to reduce accident risks, a combination method involving rank-sum ratio (RSR), criteria importance though intercriteria correlation (CRITIC), and least squares support vector machine (LVSSM) is adopted. The traffic safety risk index system and risk assessment model of ordinary arterial highways with two dimensions of risk severity and accident severity are established. Based on the global sensitivity analysis of the extended Fourier amplitude sensitivity test (EFAST), the resulting risk assessment model for ordinary arterial highways is proposed. Combined with the current traffic safety situation of ordinary arterial highways in Weinan City, Shaanxi Province, China, data collection and analyses were carried out from the perspectives of traffic operation status, personnel facilities management, road environment characteristics, and accident occurrence patterns. The results show that the risk level of ordinary arterial highways can be obviously divided into warning areas, control areas, and prompt areas. The proportion of roads through villages and the number of deceleration facilities belong to the highly sensitive indicators of the S107 safety risk, which need to be emphatically investigated. This analysis method based is on the RCLE (RSR-CRITIC-LVSSM-EFAST) risk assessment model and has high operability and adaptability. It can be adaptively divided according to the requirements of risk-level differentiation, and the road risk classification can be displayed more intuitively, which is conducive to formulating targeted improvement measures for arterial highway safety and ensuring the safe and orderly operation of arterial highway traffic.

Keywords: traffic safety; arterial highways risk assessment; risk level; RSR; CRITIC; LVSSM; EFAST sensitivity analysis

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1. Introduction

In the early stage of China's motorization development, with the annual growth of the total number of motor vehicles, traffic accidents occurred frequently. Although the improvement of safety assurance technology has effectively curbed the surge in traffic accidents in recent years, the base of road traffic accidents in China is still large, and many traffic safety problems have not been solved. Due to the special terrain, geology, and climate conditions, the technical grade of the ordinary arterial highway is low. The road is often close to water and cliffs, the line is winding, and there are many continuous curves. Many sections of continuous curves and long and large longitudinal slopes often appear at the same time. The sight distance conditions of roads, bridges, and tunnels are poor. There are many intersections with slopes along the line, and many sections pass through towns and schools. The relevant research on high-grade highways and highways in other regions has poor applicability to ordinary arterial highways with special roads and traffic environments. Highway traffic safety issues have become increasingly prominent. According to the data in [1], on ordinary arterial highways—due to the special roads they use—the particular traffic environment results in accident rates and mortality rates that are significantly higher than the average level of highways in normal areas, and more than 70% of accidents involving death and serious injury occur on ordinary arterial highways.

In order to identify the traffic safety risk status of ordinary arterial highways, clarify the relationship between risk possibility and accident severity, and take relatively effective measures to isolate road risk sources, it is necessary to comprehensively consider various risk factors. Through reasonable safety assessment and risk management methods, the risks and weak links in the arterial highway system are accurately identified, and corresponding safeguard measures are implemented to improve the traffic safety level of the ordinary arterial highway system. Therefore, highway traffic safety risk assessment methods have a positive guiding role in comprehensively evaluating road safety levels and improving traffic safety. Therefore, the research problem of this paper is how to divide the risk level of ordinary arterial highways with the risk possibility and accident severity indexes, find out the sections with high risk levels, screen the reliability dimension and severity dimension indicators that have a great impact on them, and propose safety improvement strategies.

Road traffic safety risk management research started early, but there are still many areas for improvement. In the analysis of safety risk factors, most accident causation theories summarize the main factors of accidents as unsafe human behavior or an unsafe state of things [2–6]. Modern system safety theory describes the nature of comprehensive causation from the perspective of the hazard source. There are two main types of analysis models: the Hatton matrix model and the EAI model. William Haddon put forward the famous Hatton matrix model in the 1970s, which reduced the health damage and economic loss caused by road traffic accidents and improved the road safety level from three aspects: prevention, injury reduction, and rescue. In Reference [7], the road traffic safety problem was described as the result of the combined action of three dimensions, travel exposure, accident risk, and accident consequence, and the EAI three-dimensional model was proposed, which provided a new idea for solving road traffic safety problems and reducing the degree of accident harm. The two models provide a guiding ideology for road traffic safety risk and traffic accident prevention. In terms of safety assessment, researchers have mostly established a mathematical model between traffic accidents and their influencing factors based on traffic accident statistics, so as to evaluate road traffic safety. Traffic operation status (vehicle status factors [8], driver factors [9], etc.), road environmental factors (pavement performance [10,11], road alignment [12], etc.), traffic facilities [13], accident loss [14–16], and accident risk [17] provide ideas for the establishment of a safety assessment index system.

Most of the road safety risk assessment and operation management methods use the MCDM algorithm [18] (multi-criteria decision-making). Among them, the analytic hierarchy process, the fuzzy comprehensive evaluation method, and TOPSIS are the most widely used methods in multi-objective decision-making, but these methods have certain limitations when used alone [19–22]. At the same time, in terms of project operation management, data development analysis (DEA) was found to be the most effective operation management method for mine blasting [23]. An improved entropy–TOPSIS method was proposed to evaluate the comprehensive treatment of industrial wastewater [24]. Articles [25,26] combined the fuzzy comprehensive evaluation method and analytic hierarchy process, and they proposed fuzzy–analytic hierarchy processes to determine the weight of each evaluation factor according to expert opinions. In [27], it is pointed out that the MADM method takes into account many aspects such as evaluation, prioritization, and the selection of the best alternative in the decision-making process. By looking at a section of a road after conducting a risk assessment, the road risk object can be identified. The commonly used methods include the singular value decomposition method, the cluster analysis method, the RSR method, the expert method, and the neural network method. Finally, after the risk object identification process is completed, the sensitivity analysis method is used to compare the risk objects. Parameter sensitivity analysis methods can be classified into local sensitivity analysis and global sensitivity analysis. Local sensitivity analysis is suitable for linear models or models with less uncertainty [28]. The global sensitivity analysis method analyzes the total influence of multiple parameters on the model output. Commonly used global sensitivity analysis methods include the Morris screening method [29], FAST [30], Sobol [31], and the extended Fourier sensitivity test (EFAST) [32,33]. The applicable conditions of various methods are shown in Table 1.

Table 1. Method used in this study compared with other methods.

Content	Name	Applicable Conditions
MCDM of road risk assessment [18,27]	AHP	The analytic hierarchy process is based on the evaluator's understanding of the nature and elements of the evaluation problem. It is a more qualitative analysis and judgment method than the general quantitative method. When we want to solve more common problems, the number of indicators selected is likely to increase.
	Fuzzy evaluation method	Fuzzy evaluation deals with fuzzy evaluation objects using precise digital means, and it can make a more scientific, reasonable, and practical quantitative evaluation of fuzzy information. However, the method is complex, and the determination of the index weight vector is subjective.
	TOPSIS	TOPSIS is a ranking method that approximates the ideal solution. By obtaining the proximity of each evaluation scheme to the optimal scheme, it is used as the basis for the advantages and disadvantages of the scheme.
Road risk object identification [19–26]	SVD	SVD is a widely used algorithm in the field of machine learning. It is used for feature decomposition in dimensionality reduction algorithms. It can also be used in recommendation systems, natural language processing, and other fields. In traffic, it can be used to calculate the weight of the judgment matrix in MCDM.
	Cluster analysis	Cluster analysis can be applied to a variety of research scopes, such as regional planning and risk object identification. The determination of the category level of the same type of variable is subjective and objective.
	RSR method	The RSR method is comprehensive, can show small changes, and is not sensitive to outliers. It is an effective means of comparing and finding relationships by sorting and grading each evaluation object and finding out the advantages and disadvantages.
	Expert method	The expert method is highly subjective in identifying road risk objects, as it is based on experience.
	Neural network method	The neural network method is widely used in traffic volume predictions, regression analysis, clustering analysis, etc. It has strong work randomness.
Global sensitivity analysis [29–33]	Morris	Morris is based on statistical theory, including the scatter diagram method, the correlation coefficient method, the regression analysis method, and so on. It has strong applicability to linear monotonic model analysis.
	EFAST	EFAST method is a global sensitivity analysis method based on the FAST method combined with the Sobol method. The integral required to calculate the sensitivity index becomes a single variable, saving calculation time. Each order's sensitivity index can be obtained to evaluate the coupling between several indexes.
	Sobol	Sobol is a sensitivity analysis method based on variance decomposition. As a typical global sensitivity analysis method, the Sobol method can only evaluate the coupling effect of each index with all other indexes.

Considering the comprehensiveness, complexity, and uncertainty of traffic safety risks and the applicable conditions of each evaluation method, this paper needs to find the relationship between the road risk objects and sort them; thus, the RSR method is selected, and the CRITIC method is used to calculate the weight. For global sensitivity analysis, it is necessary to find the coupling relationship between several variables, so the EFAST method is selected. In summary, this paper proposes a new road traffic safety risk assessment model: RSR–CRITIC–LVSSM–EFAST.

Through a literature review, we analyze and study safety risk assessment to find the influencing factors of accident risks, on a large scale, on traffic accident statistics. Through mathematical theory, the quantitative relationship between a single risk source and accident number is established, and a variety of models are proposed to quantitatively evaluate the risk degree of the road. Scholars have made some achievements in road risk assessment, but the following problems still exist:

1. Due to the limited data available, most of the current research focuses on the study of expressways, and there are few studies on the prediction of accident risk levels on ordinary arterial highways. However, there are many ordinary arterial highways in China, and their risk classification is an urgent problem to be solved. At the same time, the research on the risk prediction of ordinary arterial highways mostly focuses on the qualitative point of view.
2. Some models have a single risk source and lack practicality. In the analysis of the traffic accident severity, the influencing factors of traffic accidents in the current research are relatively small, and there are many factors that increase accident severity. The application scope and applicability of the model have not been fully explored.
3. Road risk assessment and operation management methods used alone have obvious shortcomings and special conditions.

The rest of the paper is organized as follows. Section 2 establishes a safety risk assessment index system considering five factors: traffic operation status, road environment, traffic facilities, accident risk, and accident loss. The risk assessment model is established by using the RCLE comprehensive method with risk possibility and accident severity as the main influencing parameters. Section 3 takes 10 ordinary arterial highways in Weinan City, Shaanxi Province, China, as an example; the road risk level is divided, the risk judgment matrix is obtained, the surrogate model is determined via LVSSM, and an EFAST sensitivity analysis is carried out. Section 4 analyzes the results of the example. Section 5 presents the conclusion and suggestions for future work.

2. Risk Assessment Model Based on RCLE

2.1. Safety Risk Assessment Index System

In view of the characteristics of complex traffic composition, poor road alignment conditions, and difficult control of the personnel management factors of ordinary arterial highways, the selection of risk assessment indicators should mainly consider the road characteristics, accident forms, environmental characteristics, and traffic safety facilities of arterial highways.

Combined with the study of traffic accidents in References [34,35] and based on road traffic safety constraints, a multi-dimensional, multi-level, and multi-factor traffic safety risk index system of ordinary arterial highways is constructed. The system includes three sub-dimensions using risk possibility as the input dimension, the traffic operation status factor, the road environment factor, and the traffic facility factor, and using accident severity as the output dimension, including two sub-dimensions: accident risk and accident loss.

Traffic operation status factors: The traffic operation status of ordinary arterial highways is relatively complex, with the characteristics of high speed limits, many types of vehicles, and road conditions resulting in the blocked state of the road and frequent accidents that interfere with road operations.

Road environment factors: The design conditions of arterial highways are limited, and unique environments are an important factor affecting the traffic safety of arterial highways. If the basic highway performance, geometric conditions, and roadside environmental conditions produce adverse combinations, they will bring a great threat to road traffic safety.

Traffic facilities factors: In a complex road environment, in terms of unfavorable road conditions and road construction funding constraints, traffic safety facilities that are set up poorly on imperfect road sections will not be able to provide the necessary security.

Accident risk: Through the analysis of road traffic accident data, we can find the law of accident occurrence, predict the degree of traffic safety risk, and further isolate the source of accident risk to improve driving safety.

Accident losses: The loss degree after the accident is closely related to road design, the management system, the rescue system, and other factors. It is necessary to adopt reasonable statistical indicators to calculate loss from traffic accidents.

2.2. Risk Judgment Matrix

The risk judgment matrix (R matrix) is based on risk possibility and accident severity as the main influencing parameters. According to the frequency and characteristics of traffic accidents on ordinary arterial highways, the CRITIC method and RSR method are used to process the indicators, the traffic risk and accident consequences are divided into degrees, and the logical relationship between the elements is established in a matrix mode. The form of the risk judgment matrix is shown in Table 2.

Table 2. Risk discriminant matrix.

Accident Severity	**Risk Possibility**		
	Acceptable Risk (Low Risk)	**Tolerable Risk (Medium Risk)**	**Intolerant Risk (High Risk)**
Light loss	Low risk of accidents, minor consequences (R_{11}) *	Accidents not frequent, minor consequences (R_{12}) **	Accident-prone, minor consequences (R_{13}) ***
Acceptable loss	Low risk of accidents, acceptable consequences (R_{21}) **	Accidents not frequent, acceptable consequences (R_{22}) ***	Accident-prone, acceptable consequences (R_{23}) ****
Heavy loss	Low risk of accidents, serious consequences (R_{31}) ***	Accidents not frequent, serious consequences (R_{32}) ****	Accident-prone, serious consequences (R_{33}) *****

* represents the road safety risk level is light, ** represents the road safety risk level is low, *** represents the road risk level is medium, **** represents the road risk level is high, ***** represents the road safety risk level is heavy.

From the single-dimension direction of the R matrix, the degrees of risk and loss are divided into three levels, from light to heavy. In the process of interaction between the two, from the upper left corner to the lower right corner of the R matrix, the increase in the number of * indicates that the road safety risk level is rising and presents different road hazards. In general, the classification matrix can be roughly divided into three parts: the upper left area (area I) is the risk prompt area, the area near the diagonal is the risk control area (area II), and the lower right area is the risk warning area (area III). In the actual operation process, the risk possibility level and the accident severity level can be further refined into z $(z > 3)$ levels according to design needs and grade differentiation needs to obtain an ideal road risk level.

When the degree of road risk is determined, the design and implementation of safety measures are carried out according to the results of risk classification and sensitivity analysis. On the premise of safety, the flexibility of facilities is used to bear higher loss risk so as to reduce the probability and severity of accidents.

2.3. Risk Assessment Model

After comprehensively analyzing the advantages and disadvantages of each method and optimizing them, this paper proposes a risk assessment model based on RCLE. Through the hybrid model, the data-processing and benchmarking analysis of risk objects are carried out. The calculated possibility and severity dimension rank and ratio are used as the basis for the classification of risk input and accident output, and the risk judgment matrix is constructed. The road risk level calculation results are classified into the R matrix to determine the risk level of the road. Secondly, considering the randomness of parameters, the surrogate model of LSSVM is established. Finally, through the model analysis and evaluation results, we can find the safety benchmark objects and risk sensitivity factors and put forward the corresponding traffic safety improvement measures and implementation order in order to use less investment to obtain greater safety gains, reducing the overall level of regional road risk. The calculation process and steps of the RCLE model are as follows:

1. Initial risk matrix

According to the road traffic safety risk index system, combined with the actual survey data, the initial risk matrix, A, is established as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{n2} & \cdots & a_{mn} \end{bmatrix} \tag{1}$$

where m represents the number of risk assessment objects; n represents the number of risk indicators (it contains k—possibility dimension indicators—and s—severity dimension indicators); and a_{mn} represents the risk object, m, and the value of the n risk indicator.

2. Risk matrix standardization

In the traffic safety risk index system, there are positive indicators (such as pavement skid resistance, smoothness, etc.) and negative indicators (such as bad linear ratio, overloaded vehicle ratio, etc.). In order to keep the same change trend and eliminate the dimensional influence, for traffic safety positive indexes, the conversion method is as follows:

$$x'_{ij} = \frac{x_{ij} - mix(x_j)}{max(x_j) - \min(x_j)} \tag{2}$$

For the negative effect indexes, the conversion method is

$$x'_{ij} = \frac{max(x_j) - x_{ij}}{max(x_j) - \min(x_j)} \tag{3}$$

To obtain the standardized matrix, $y_{ij} = \left(x'_{ij}\right)_{m\times n}$, where x_{ij} represents the i risk object in Y and the value of the j risk indicator, in which $i = 1, 2, \cdots, m$, $j = 1, 2, \cdots, n$.

3. Index weight by CRITIC

We can calculate the standard deviation of each index and the linear correlation coefficient between the indexes, obtain the amount of information contained in the evaluation index, and determine the weight coefficient of the index:

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_{ij} - \mu_j)} \tag{4}$$

$$C_j = \sigma_j \sum_{i=1}^{n}\left(1 - r'_{ij}\right) \tag{5}$$

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{6}$$

where σ_j represents the standard deviation of indicator j, μ_j represents the expected value of indicator j, r'_{ij} represents the linear correlation coefficient of indicator i and indicator j, C_j represents the information on indicator j, and w_j represents the weight of indicator j.

4. Write ranks and calculate weighted rank-sum ratio

The nonintegral RSR method is used to rank the risk matrix after assimilation. For m, the risk evaluation objects are sorted according to the size of the index value; the maximum observation value is given m as a rank, the minimum observed value is given 1 as a rank, and the remaining index values are ranked by similar linear interpolations.

$$r_{ij} = 1 + (m-1)\frac{x'_{ij} - x'_{jmin}}{x'_{jmax} - x'_{jmin}} \tag{7}$$

where r_{ij} represents the rank of the j indicator of the i risk object, x'_{jmin} represents the minimum of the j indicator value, and x'_{jmax} represents the maximum of the j indicator value.

After calculating the risk rank matrix, Z, the input dimension weighted rank-sum ratio, α; the output dimension weighted rank-sum ratio, β; and the risk evaluation individual weighted rank-sum ratio, γ, are calculated as follows:

$$Z = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{n2} & \cdots & r_{mn} \end{bmatrix} \tag{8}$$

$$\begin{cases} \alpha_i = \frac{1}{m} \sum\limits_{j=1}^{p} r_{ij} w_j \\ \beta_i = \frac{1}{m} \sum\limits_{j=1}^{l-p} r_{ij} w_j \\ \gamma_i = \frac{1}{m} \sum\limits_{j=1}^{l} r_{ij} w_j \end{cases} \tag{9}$$

where α_i represents the possibility dimension weighted rank-sum ratio of the i risk object, β_i represents the severity dimension weighted rank-sum ratio of the i risk object, γ_i represents the individual weighted rank-sum ratio of the i risk object, and l,p represents the intermediate variable.

5. Determine the rank and ratio distribution

According to the small and large values of α, β, and γ, they are arranged separately. The same values are taken as a group. The frequency, f, and cumulative frequency, $f\downarrow$, of each group are listed, and the rank range and average rank, R, of each group are determined. After calculating the cumulative frequency, $\bar{R}/m \times 100\%$ (the cumulative frequency of the last group is set to $1 - 1/(4m)$), the probability unit value, Y, corresponding to the percentile is listed according to the percentile and its corresponding probability unit table.

6. Calculate regression equation

The values of α, β, and γ are used as dependent variables (represented by R_{SR}), and the corresponding probability unit value, Y, is used as an independent variable to estimate the regression equation. The error analysis is carried out to ensure that the regression equation has significant statistical significance.

$$R_{SR} = a + bY \tag{10}$$

where a,b represents the estimate of the parameters.

7. Construct a risk judgment matrix

According to the actual situation, the optimal number of groups of α,β,γ is selected. According to the different number of groups, the corresponding percentiles and their probability unit values are listed, and the interval is calculated according to Formula (11):

$$R^*_{SR} = a + bY^* \tag{11}$$

where R^*_{SR} represents the rank-sum ratio calculated by probability unit, Y^*. Y^* represents the probabilistic unit value corresponding to the number of groupings. c,d represents the estimate of the parameters.

According to the reasonable grouping method in the RSR method [36], the risk judgment matrix was constructed by using the grading values of α and β as the grading standards of risk possibility and accident severity, respectively. At the same time, the variance consistency test and variance analysis were carried out to ensure that the archived groups were statistically significant and that there were significant differences between groups.

8. Road risk judgment

After the judgment model is constructed, each risk evaluation object after grouping is classified into the R matrix according to the scores of α and β, and the degree of road safety risk is judged to determine the priority of the implementation of safety and security measures.

9. Surrogate model based on LSSVM

The surrogate model can be understood as a mathematical model that predicts unknown responses by performing regression or interpolation on discrete datapoints through approximation techniques, with fitting accuracy as a constraint. The least squares support vector machine transforms the support vector machine problem into linear equations that can be used as solutions to improve the solution speed and reduce memory usage. At the same time, the error square sum loss function of the training sample is used as the empirical loss, which improves the convergence accuracy of the model [37] and is one of the most commonly used surrogate models.

From the above, RSR obtains the α,β,γ regression equation, and the LSSVM linear model can be obtained: let the sample be an n-dimensional vector, and the N samples are $(\alpha_1, Y_1)(\alpha_2, Y_2), \cdots, (\alpha_N, Y_N) = (x_1, Y_1)(x_2, Y_2), \cdots, (x_N, Y_N) \in R^n \times R$. The data can be mapped from the original space, R^n, to the high-dimensional space, $\varphi(x_k)$, through the kernel function, and the data can be obtained: $Y(x) = \omega\varphi(x_k) + b$, according to the structural risk minimization.

$$\begin{cases} minJ(\omega, e) = \frac{1}{2}\omega^T\omega + c\sum\limits_{k=1}^{N} e_k^2 \\ s.t. y_k = \omega^T\varphi(x_k) + b + e_k, k = 1, \cdots, N \end{cases} \tag{12}$$

where c represents the regularization parameter, e_k represents the relaxing factor, and ω,b represents the coefficients.

Introducing the kernel function, $K(x, x_k) = \varphi(x_k)\varphi(x) = \Omega_i$, and using the Lagrange method to solve Equation (12), we have

$$\begin{bmatrix} 0 & 1_v^T \\ 1 & \Omega + c^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \tau \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{13}$$

where τ represents the Lagrange multiplier.

Using the least square method to solve Equation (13), we can obtain the following:

$$Y(x) = \omega\varphi(x_k) + b = \sum_{k=1}^{N} \tau_k K(x, x_k) + b \tag{14}$$

The validity of the LSSVM fitting results is tested as follows:

$$e_i = \left| \frac{Y_i - Y_i'}{Y_i} \right| \tag{15}$$

$$M = \frac{1}{n}\sum_{i=1}^{n}(1 - e_i) \tag{16}$$

where Y_i represents the true value of the i sample, Y_i' represents the test value of the i sample, e_i represents the relative error, and M represents availability.

10. EFAST sensitivity analysis

By using the surrogate model and the sensitivity analysis of the risk possibility influencing factors, the high-risk sensitivity indicators are found and further sorted, and then the traffic safety improvement strategies are put forward. This paper uses the extended Fourier sensitivity test (EFAST), which is a global sensitivity analysis method based on variance [26]. On the basis of the Fourier amplitude sensitivity test, combined with the idea of Sobol variance decomposition, the first-order and high-order sensitivity indexes can be calculated. The number of sampling times [27] is related to the number of influencing factors considered, and the calculation amount is relatively small and has good robustness.

The variance of the input parameter, X_{it}, is denoted by V_i; the variance of the interaction between the input parameters is denoted by $V_{i,j}$, $V_{i,j,m}$, and $V_{i,j,\cdots,k}$; and the total output variance is denoted by V. The first-order sensitivity index, S_i (main utility), of X_{it} is

$$S_i = \frac{V_i}{V} \tag{17}$$

Higher-order sensitivity indices caused by the interaction of X_{it} and other input parameters are as follows:

$$\begin{cases} S_i = \frac{V_{i,j}}{V} \\ S_{i,j,m} = \frac{V_{i,j,m}}{V} \\ S_{i,j,\cdots,k} = \frac{V_{i,j,\cdots,k}}{V} \end{cases} \tag{18}$$

This contains the total utility, S_{Ti}, of the sum of the contribution of X_{it} and its interaction with the total variance, which can be expressed as

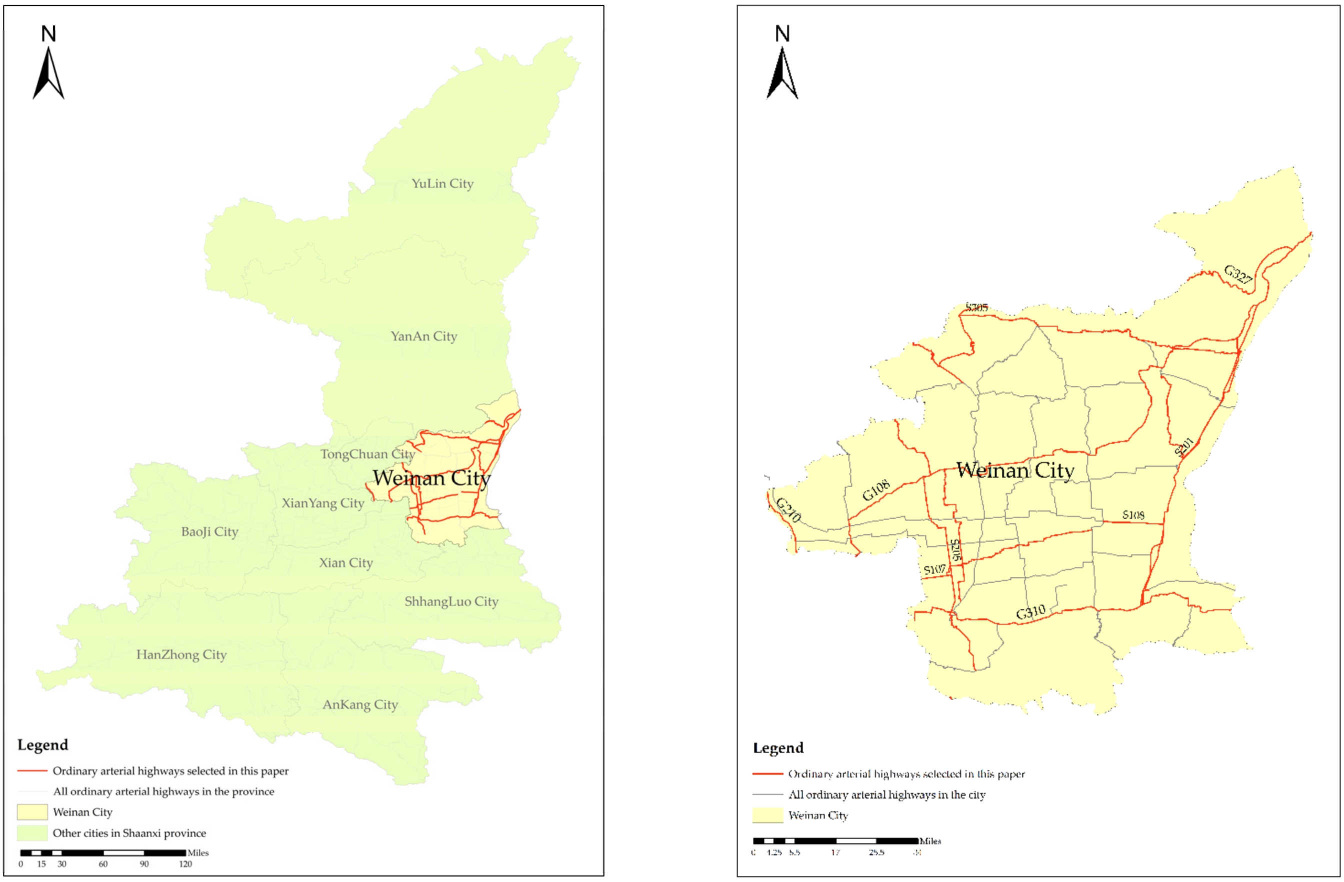
$$S_{Ti} = S_i + S_{i,j} + S_{i,j,m} + \cdots + S_{i,j,\cdots,k} \tag{19}$$

The high-sensitivity risk factors are determined by sorting the total utility sensitivity values.

3. Case Study

3.1. Profile

Weinan City is located in Shaanxi Province, China, and is the junction of Shaanxi, Henan, and Shanxi Provinces. Weinan's terrain up to the Weihe River is an axis; two mountains are in the north and south, as well as two plateaus and central plains and five major types of landforms. Through the investigation of the road network distribution status and road network development planning of the arterial highways in the Weinan area, considering factors such as terrain and natural conditions in the Weinan area, this paper selects G310, G3108, G327, G210, S209, S107, S108, S201, S205, and S305, which are typical ordinary arterial highways, combined with traffic operation data and accident data from January to June 2021, for case analysis. The location is shown in Figure 1.



(**a**) (**b**)

Figure 1. Selected highway locations map. (**a**) Location in Shaanxi, China; (**b**) location in Weinan, Shaanxi.

3.2. Evaluating Indicators

Through the field survey, according to the easy collection and accuracy of the data, the indicators that can reflect the characteristics of the arterial highway are selected to construct the safety risk evaluation index system. In the actual operation process, because the object of the risk analysis is the whole road section, the index selection mainly focuses on the macro quantitative index and does not evaluate the micro road linearity. The selection and calculation of specific indicators are shown in Figure 2.

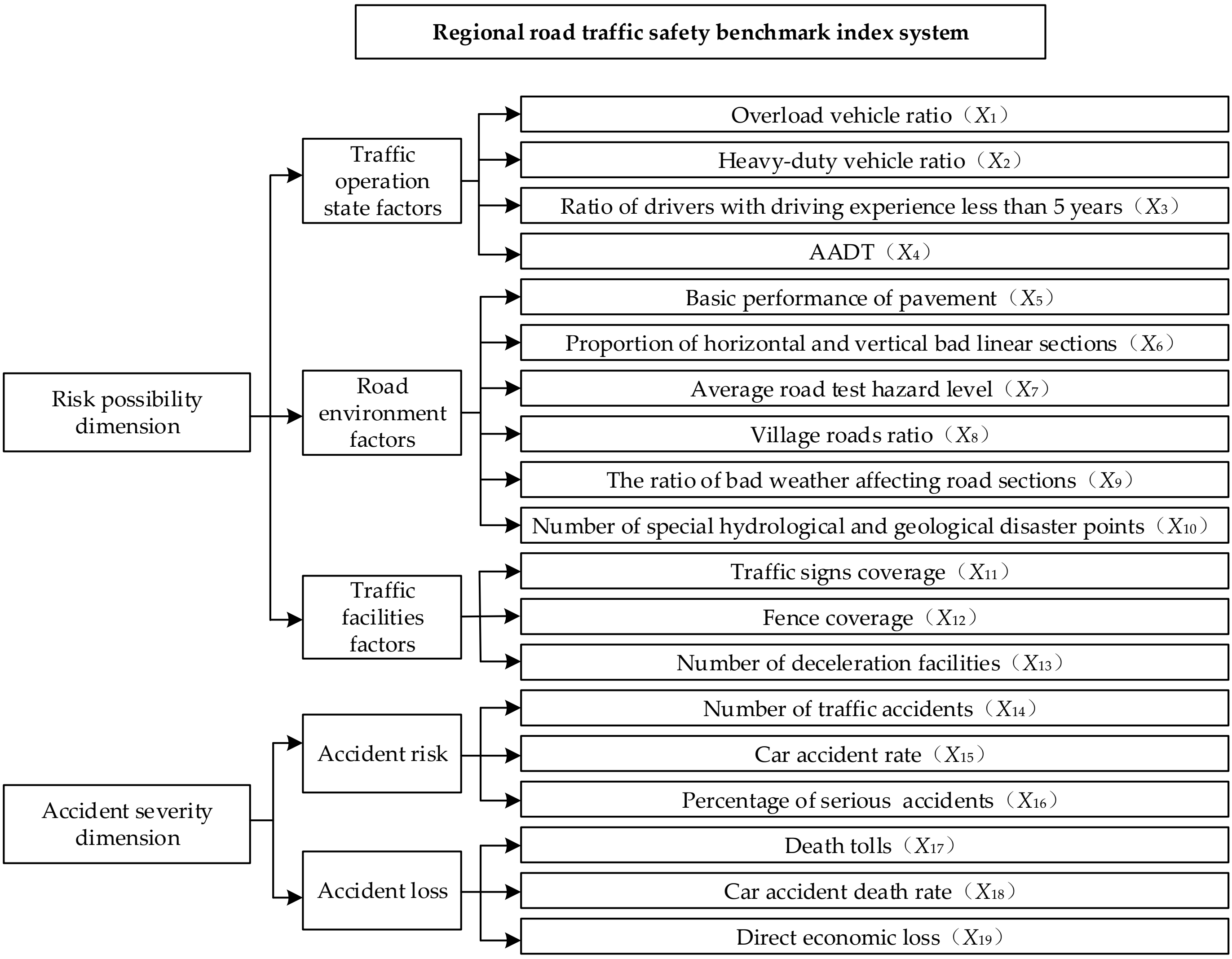


Figure 2. Index system of road traffic safety risk.

The road traffic safety risk index system includes qualitative indicators and quantitative indicators. The evaluation criteria and acquisition methods of some indicators are shown in Table 3.

3.3. Risk Assessment

Taking 10 ordinary arterial highways in Weinan City as an example, the risk assessment of road safety is carried out by establishing a risk assessment model based on RCLE. After obtaining the basic data required by the index system, the initial risk matrix is constructed (Table 4), and the initial matrix is standardized.

In order to find the relative connection strength between each index, the CRITIC method is used to calculate the weight value of the index, and the results are shown in Table 5.

According to the rules of the rank-sum ratio method, the index values of each risk factor are ranked, and the weighted rank-sum ratios are calculated, as shown in Table 6.

Table 3. Index calculation methods.

Index	Meaning	Evaluation Methods
X_1	Overload vehicle ratio	$X_1 = \frac{a_1}{b_1}$. The number of overloaded vehicles, a_1, and the total number of vehicles, b_1, in the sampling survey.
X_2	Heavy-duty vehicle ratio	Statistics of vehicles in the traffic flow by vehicle type, of which heavy vehicles include large trucks, very large trucks, and container trucks.
X_3	Ratio of drivers with driving experience less than 5 years	$X_3 = \frac{a_3}{b_3}$. Drivers with more than 5 years of driving experience in sample survey, a_3; total drivers' sample, b_3.
X_4	AADT	Provided by traffic flow observation stations in highway networks.
X_5	Basic performance of pavement	The basic performance of the pavement includes flatness, a_5; skid resistance, b_5; lane width, c_5; and shoulder width, d_5. $X_5 = a_5b_5c_5d_5$
X_6	Proportion of horizontal and vertical bad linear sections	Poor linear sections of horizontal and vertical sections include sharp bends, steep slopes, continuous downhills, poor sight distance sections, and their combinations.
X_7	Average road test hazard level	The roadside danger degree is divided into four grades according to the width of the roadside clear area, slope grade, and roadside dangerous goods.
X_8	Village roads ratio	$X_8 = \frac{a_8}{b_8}$. Length of road through village, a_8; total length of road, b_8
X_9	The ratio of bad weather affecting road sections	Effect of cloudy, rainy, snowy, fog, high-temperature, freezing, dust, and other adverse weather conditions such that the driver's line of sight is blocked; the road adhesion coefficient decreased and the road length accounted for the proportion of the total road length.
X_{10}	Number of special hydrological and geological disaster points	According to data from monitoring stations, the affected road sections of disasters such as earthquakes, landslides, collapses, debris flows, and roadbed subsidence are counted.
X_{11}	Traffic signs coverage	Number of traffic signs per kilometer of road included.
X_{12}	Fence coverage	Proportion of road length covered by roadside guardrails.
X_{13}	Number of deceleration facilities	The deceleration setting includes deceleration markings, vibration deceleration belts, three-dimensional deceleration markings, etc.
X_{14}–X_{19}	Severity dimension indicators represent the number of traffic accidents, car accident rates, percentage of serious accidents, death tolls, car accident death rates, and direct economic loss.	Severity dimension indicators can be provided by the Highway Authority.

After determining the weighted rank-sum ratio, the correlation and regression analyses of the dependent variable, α,β,γ, and the independent variable, Y, are performed, and the results are shown in Table 7.

Table 4. Initial risk matrix.

Index	Ordinary Arterial Highway Number									
	G310	**G108**	**G327**	**G210**	**S209**	**S107**	**S108**	**S201**	**S205**	**S305**
X_1	0.0145	0.0278	0.0136	0.0249	0.1652	0.2108	0.1725	0.2519	0.1568	0.1818
X_2	0.1071	0.1009	0.1803	0.1201	0.1317	0.2245	0.1146	0.1869	0.1245	0.1221
X_3	0.5861	0.5365	0.5219	0.5488	0.6017	0.5932	0.5346	0.6105	0.6033	0.6045
X_4	1341	1928	4485	5624	6007	1668	1874	5546	2815	1457
X_5	1.78	0.77	1.66	1.52	1.99	1.66	2.39	2.74	1.21	1.32
X_6	0.1047	0.0431	0.0229	0.0781	0.171	0.1481	0.0125	0.0199	0.1321	0.0257
X_7	0.1925	0.1604	0.1568	0.2465	0.6126	0. 1176	0.381	0.0901	0.3925	0.2489
X_8	0.037	0.2819	0.1547	0.1324	0.3025	0.4025	0.2198	0.264	0.4554	0.3215
X_9	0.5056	0.0707	0.1357	0.3458	0.312	0.4025	0.2198	0.264	0.4554	0.3217
X_{10}	42	31	25	16	8	66	21	4	52	31
X_{11}	4.5945	3.0433	4.1571	3.1245	3.3978	1.775	2.3432	2.1869	2.456	2.647
X_{12}	0.2885	0.3652	0.4863	0.4332	0.5997	0.2449	0.487	0.1131	0.4882	0.3214
X_{13}	18	16	12	13	6	5	8	7	2	1
X_{14}	45	82	12	20	121	245	33	26	21	84
X_{15}	0.0568	0.625	0.0128	0.0267	0.5519	4.0242	0.04824	0.3214	0.2524	0.6932
X_{16}	0.5	0.2837	0.2347	0.3645	0.0331	0.0286	0.0606	0.3461	0	0.1247
X_{17}	2	3	1	4	11	18	9	5	0	6
X_{18}	0.0284	0.226	0.1234	0.3415	0.0182	0.1807	0.0292	0.0445	0	0.2315
X_{19}	15,150	668.47	6549	2142	235	114.08	92.22	120.15	2.3	203

Table 5. Index weights.

Index	Weight	Index	Weight
X_1	0.0548	X_{11}	0.0452
X_2	0.0487	X_{12}	0.0476
X_3	0.0530	X_{13}	0.0490
X_4	0.0797	X_{14}	0.0392
X_5	0.0525	X_{15}	0.0408
X_6	0.0529	X_{16}	0.0744
X_7	0.0573	X_{17}	0.0416
X_8	0.0418	X_{18}	0.0617
X_9	0.0465	X_{19}	0.0672
X_{10}	0.0461		

Table 6. Values of rank-sum ratio.

Ordinary Arterial Highway Number	Possibility Dimension α	Severity Dimension β	Individual Dimension γ
G310	0.705	0.582	0.666
G108	0.738	0.674	0.719
G327	0.732	0.768	0.745
G210	0.629	0.643	0.632
S209	0.462	0.824	0.575
S107	0.397	0.534	0.448
S108	0.714	0.884	0.764
S201	0.506	0.792	0.591
S205	0.425	0.988	0.601
S305	0.557	0.742	0.608

Table 7. Results of correlation and regression analysis.

Variable	Regression Equation	Correlation Coefficient r	Significance Level p
α	$\alpha = 0.128Y - 0.077$	0.997	0.00001519
β	$\beta = 0.140Y + 0.017$	0.9679	0.00003481
γ	$\gamma = 0.091Y + 0.162$	0.9815	0.000008897

In Table 7, it can be seen that the correlation coefficient, r, between the dependent variable and the independent variable is greater than 0.967, so it can be judged that the two have an obvious linear correlation. Via the F test, the significance level, p-value, does not exceed 0.0005; therefore, the linear regression equation has statistical significance. According to the reasonable classification method of RSR, the weighted rank-sum ratio is classified, and the R matrix is constructed. According to the actual requirements, the weighted rank-sum ratio of different dimensions is divided into five grades, and the road risk evaluation object is classified into the R matrix. The risk level of the road evaluation object is divided, which is used to analyze and evaluate the safety risk degree of the road. The results are shown in Table 7.

4. Analysis of Evaluation Results

By calculating the rank-sum ratio of the two dimensions of risk possibility and accident severity, the risk degree of each road is reasonably divided. The chromaticity difference calibrated in the matrix is used to assist in the judgment of the degree of risk, so as to more intuitively show the level of risk faced by the evaluation object, and accordingly determine the urgency of each road safety improvement demand. From the relationship matrix in Table 8, it can be seen that the risk ranking of ordinary arterial highways in Weinan City is mainly divided into three gradients: S107 and G310 are located in the risk warning area; S205, S209, G327, G210, S201, and S305 are located in the risk control area; and S108 and G108 are located in the risk warning area. S107 is in the position with the deepest color, indicating that the possibility of accidents is higher; the degree of loss after the accident is more serious, the risk level is the highest, and the corresponding safety and security measures need to be taken into account first. In contrast, the risk level of G209 and G327 is slightly higher than that of S108 and G108, and the lowest risk level is S108.

Table 8. Relation matrix (R matrix).

Severity Dimension β_i	Possibility Dimension α_i				
	Light Risk (>0.791)	Low Loss (0.638~0.791)	Medium Risk (0.485~0.638)	Higher Level of Risk (0.332~0.485)	High Risk (<0.332)
Light loss (>0.967)				S205	
Low level of loss (0.800~0.967)		S108	S209		
Medium loss (0.632~0.800)	G108	G327	G210, S201, S305		
Higher level of loss (0.464~0.632)			G310	S107	
Heavy loss (<0.464)					

4.1. LSSVM Fitting Results

After determining the risk level and the implementation order of traffic safety guarantee measures, the key investigation sections are selected. This paper selects S107 and S108 for comparative analysis and obtains the probability distribution of the risk possibility index influencing factors. The data distribution characteristics are as follows in Table 9. We then use EFAST to observe the sensitivity of each risk possibility influencing factor of the evaluation object.

Table 9. Distribution characteristics of the risk possibility index.

Index	Mean Value *	Standard Deviation	Diversity	Dispersion Pattern
X_1	1.388	0.191	0.137	Uniform
X_2	1.082	0.131	0.121	Uniform
X_3	1.085	0.078	0.072	Uniform
X_4	1	0.03	0.03	Uniform
X_5	1	0.012	0.012	normal
X_6	1.015	0.05	0.05	normal
X_7	0.999	0.044	0.043	normal
X_8	0.788	0.044	0.044	Uniform
X_9	1.09	0.085	0.108	Uniform
X_{10}	1.131	0.031	0.028	Uniform
X_{11}	1.034	0.032	0.022	normal
X_{12}	1.321	0.045	0.036	normal
X_{13}	1	0.065	0.065	normal

* The mean value is the actual value/standard value.

According to the probability distribution characteristics of Table 9, 100 Monte Carlo samplings were carried out on the influencing factors by multiplying the 3 coefficients of 0.7, 1.0, and 1.3 to explore whether the dispersion degree of the variables had an impact on the evaluation index, taking 30 samples from each group of the above calculation results as training samples for LSSVM modeling and taking 20 samples from each group as test samples to test the model effectively. An effective LSSVM model is used to expand the sample data for global sensitivity analysis.

In Table 10, it can be seen that LSSVM has a good fitting effect, the residuals are tested by the lillietest function of MATLAB, and the return values are all zero, so the results are credible. In addition, taking the S107 index under the condition of the minimum covariance of the influencing factors as an example, the difference between the true value and the predicted value of the test sample of the LSSVM model is compared using a scatterplot (Figure 3). The figure can intuitively reflect the difference between the real value and the predicted value. It can be seen in Figure 3 that, except for individual abnormal points, the real value and the predicted value in each case are very close, and some points even completely coincide, indicating that the surrogate model has an excellent fitting effect.

Table 10. LSSVM model effective.

Availability	Small Covariance	Medium Covariance	Large Covariance
Y_{S107}	0.99	0.099	0.98
Y_{S108}	0.96	0.97	0.96

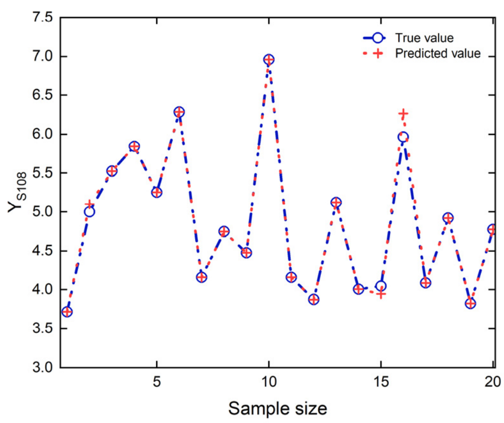
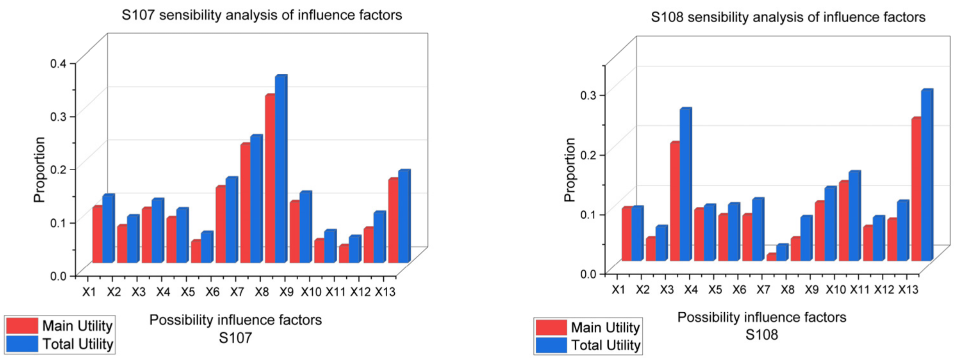


Figure 3. Test sample scatter comparison.

4.2. EFAST Global Sensitivity Analysis

The input parameter samples are generated on the Simlab platform (sensitivity analysis software), and the result parameters are output by LSSVM. Each group of 845 samples generates a total of 13 groups, forming the entire sample space. On this basis, the EFAST method is used to calculate the first-order sensitivity index (main utility) of each parameter and the high-order total sensitivity index (total utility), including the interaction with other parameters. We draw a sensitivity diagram index for S107 and S108, as shown in Figure 4.



(**a**) (**b**)

Figure 4. S107 and S108: sensitivity of each evaluation index. (**a**) S107 sensitivity analysis; (**b**) S108 sensitivity analysis.

In Figure 4, red indicates the main utility, and blue corresponds to the total utility. Since the total utility contains the main utility of the single factor and the utility caused by the interaction between factors, the total utility is not less than the main utility. From the 3a analysis, it can be seen that the sensitivity of S107's risk possibility dimension risk indicators, X_6 (poor linear ratio of horizontal and vertical), X_7 (proportion of roadside dangerous sections), X_8 (proportion of village roads), and X_{13} (number of deceleration facilities), is relatively high, and these are part of S107's safety risk sensitivity indicators. From the analysis of 3b, it can be seen that the sensitivity of S108's risk possibility dimension risk indicators, X_3 (driver ratio of no more than 5 years), X_{11} (traffic sign coverage), and X_{13} (number of deceleration facilities), is relatively high, and these are part of S108's safety risk sensitivity indicators.

4.3. Analysis and Discussion

This paper proposes a new road risk assessment and global sensitivity analysis model, which can effectively identify the risk points of ordinary arterial highways, refine the risk level, and conduct benchmarking analyses on roads with obvious risk differences. The LSSVM and EFAST models are used to identify the sensitivity between the parameters. According to the road risk sensitivity factors, corresponding traffic safety guarantee measures are taken to improve the accuracy and effectiveness of the risk response measures formulated by the traffic managers so as to obtain the highest safety return with minimum investment, reduce safety risk to a large extent, improve the road safety, and ensure the life and property safety of road participants.

Based on the analysis of 10 ordinary arterial highways in Weinan City, a risk assessment model is constructed by considering the driver, road, and traffic environment factors with respect to the risk possibility, accident risk, and the accident severity loss and 5 levels and 19 indicators. This method is similar to the safety hazard method of the high-speed horizontal and vertical curve combination section in Reference [38]. Using the multi-objective decision-making method to determine the risk level of different sections, this paper puts the roads into the matrix and intuitively presents the risk degree of each road. Among them, S108 and G108 have the lowest risk degrees, while S107 is in the darkest warning area with the highest risk level, so it is necessary to give priority to safety remediation measures.

Further sensitivity analysis shows that the roadside environment has a significant impact on the traffic safety of ordinary arterial highway road S107. The data show that the sensitivity of the proportion of the village road is the highest, and the main utility and total utility are more than 0.3. The results are similar to those in the literature [39,40]. Through the LSSVM and EFAST methods, the real value and the predicted value of the model are first fitted. It can be found that, except for individual abnormal points, the real value and the predicted value in each case are very close, and some points even completely coincide, indicating that the surrogate model has an excellent fitting effect. The global sensitivity analysis of S107 showed that $X_8 > X_7 > X_{13} > X_6 > X_9 > X_1 > X_3 > X_4 > X_2 > X_{12} > X_{10} > X_5 > X_{11}$. Therefore, the proportion of roads through villages is the most sensitive, and the improvement of measures for this factor can obtain higher risk returns. The number and scope of extreme geographical environments where roads are located are highly sensitive indicators, which need to be focused on. Under the condition that the road route is difficult to change, for the S107 road with the highest risk level, a village prompt sign and a deceleration facility can be first added to the position where it passes through the village, and the continuity of the guardrail setting should be paid attention to in order to remind the driver of the condition changes in the road ahead. The monitoring and management of geological disaster points should be strengthened. In special weather, the traffic flow should be reasonably dredged, and the number of patrols at special environmental points should be increased. When road damage occurs, the speed of repair should be accelerated. Special risk investigations and assessments for dangerous roadside sections should be conducted, and better traffic safety measures should be taken. Traffic safety facilities have a significant impact on the traffic safety of ordinary arterial highway road S108. According to its global sensitivity, we found that only the main effect and total effect of X_{13} (number of deceleration facilities) exceed 0.2, and the order is as follows: $X_{13} > X_3 > X_{10} > X_9 > X_1 > X_4 > X_6 > X_5 > X_{12} > X_{11} > X_8 > X_2 > X_7$. Therefore, factors with great influence are found, and the analysis of high-risk sensitivity indicators can provide necessary guidance for the implementation of road safety improvement measures so as to reduce the road risk level and improve road traffic safety.

In addition, the RLCE risk assessment model of ordinary arterial highways proposed in this paper has some limitations. On the one hand, the article focuses on the two dimensions of risk possibility and accident severity, considering the five factors of traffic operation status, road environmental factors, traffic facilities, accident risk, and accident loss. However, the driver is a key factor. Due to the lack of data, this paper only considers the driving age, that is, 'Ratio of drivers with driving experience of less than 5 years'. In other traffic accident studies, the possibility of risk and the severity of the accident are affected by the gender, age, and driving characteristics of the traffic participants [41]. In particular, some studies confirm that drivers with reckless driving characteristics are more prone to collisions. On the other hand, with regard to hazardous meteorological factors, some studies have pointed out that, although not the main factor in traffic accidents, they are an important modifying factor [42]. Therefore, further statistical analysis of the above two aspects of the experimental section will help to determine the key factors affecting traffic incidents, extract more comprehensive accident indicators, and further improve the accuracy of the model.

5. Conclusions

Based on the analysis of the characteristics of ordinary arterial highways, this paper establishes a targeted road safety risk index system. Through the construction of the risk assessment model, the road risk level is adaptively divided according to the needs of the evaluation object. Through the model calculation results and combined with the color difference auxiliary judgment, the intuitive description of different risk levels is completed, which is more conducive for decisionmakers to intuitively understand the road safety situation.

Through RSR and CRITIC, the road is classified into a risk relationship matrix, and the LSSVM and EFAST methods are used to analyze the influencing factors of road safety in detail, find the risk index agent model, determine the sensitive risk factors, and take this as a guide. Corresponding safety improvement measures to reduce the risk of road accidents can then be put forward.

In the case of ordinary arterial highways in Weinan City, Shaanxi Province, the road risk level is divided. Through the analysis of calculation results, we found that geological disasters and roadside safety hazards are the main factors affecting the overall safety of the S107 road, and improvement measures to reduce road safety risks are put forward.

In a follow-up study, the traffic participants can be further evaluated and analyzed from the perspective of management, and the impact factors can be determined to provide the necessary theoretical basis for the improvement of the traffic safety of ordinary arterial highways.

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References

1. Yang, Y.; Jin, L. Visualizing Temporal and Spatial Distribution Characteristic of Traffic Accidents in China. *Sustainability* **2022**, *14*, 13706. [CrossRef]
2. Raghvendra, V.C.; Joseph, H.S. Coordinability and Consistency: Application of Systems Theory to Accident Causation and Prevention. *J. Loss Prevent. Proc.* **2015**, *33*, 200–212.
3. Abraha, H.H.; Liyanage, J.P. Review of Theories and Accident Causation Models: Understanding of Human-Context Dyad Toward the Use in Modern Complex Systems. In Proceedings of the 7th World Congress on Engineering Asset Management, Deajeon City, Republic of Korea, 8–9 October 2012; Springer: Berlin, Germany, 2015; pp. 17–32.
4. Kageyama, I.; Kuriyagawa, Y.; Haraguchi, T.; Kaneko, T.; Nishio, M.; Watanabe, A. Study on Road Friction Database for Traffic Safety: Construction of a Road Friction-Measuring Device. *Inventions* **2022**, *7*, 90. [CrossRef]
5. Khattak, A.; Almujibah, H.; Elamary, A.; Matara, C.M. Interpretable Dynamic Ensemble Selection Approach for the Prediction of Road Traffic Injury Severity: A Case Study of Pakistan's National Highway N-5. *Sustainability* **2022**, *14*, 12340. [CrossRef]
6. Abdullah, P.; Sipos, T. Drivers' Behavior and Traffic Accident Analysis Using Decision Tree Method. *Sustainability* **2022**, *14*, 11339. [CrossRef]
7. Nasibeh, A.F.; Anna, S.; Ehsan, R.; Jaime, A.C. Risk Assessment of Occupational Injuries Using Accident Severity Grade. *Saf. Sci.* **2015**, *76*, 160–167.
8. Ye, X.; Pendyala, R.M.; Shankar, V.; Konduri, K.C. A Simultaneous Equations Model of Crash Frequency by Severity Level for Freeway Sections. *Accid. Anal. Prev.* **2013**, *57*, 140–149. [CrossRef]
9. Mujalli, R.O.; De, O.J. A Method for Simplifying the Analysis of Traffic Accidents Injury Severity on Two-lane Highways Using Bayesian Networks. *J. Saf. Res.* **2011**, *42*, 317. [CrossRef]
10. Msallam, M.; Asi, I.; Abudayyeh, D. Safety Evaluation (Skid Resistance) of Jordan's National Highway Network. *Jordan J. Civ. Eng.* **2019**, *11*, 2017–2165.
11. Hussein, N.; Hassan, R.; Fahey, T. Effect of Pavement Condition and Geometrics at Signalised Intersections on Casualty Crashes. *J. Saf. Res.* **2021**, *76*, 276–288. [CrossRef]
12. Khattk, A.J.; Shamayleh, H. Highway Safety Assessment Through Geographic Information System-based Data Visualization. *Comput. Civil Eng.* **2005**, *19*, 407–411. [CrossRef]
13. Transportation Association of Canada. *Drag Model Approach: Developments and Applications*; Transportation Research Board: Washington, DC, USA, 2002.

14. Charly; Mathew. Evaluation of Driving Performance in Relation to Safety on an Expressway Using Field Driving Data. *Transp. Lett.* **2020**, *12*, 340–348. [CrossRef]
15. Orsini, F.; Gecchele, G.; Gastaldi, M.; Rossi, R. Large-scale Road Safety Evaluation Using Extreme Value Theory. *IET Intell. Transp. Sy.* **2020**, *14*, 1004–1012. [CrossRef]
16. Alfonso; Montella. Safety Reviews of Existing Roads: Quantitative Safety Assessment Methodology. *Transport. Res. Rec.* **2018**, *1922*, 62–72.
17. Ait-Mlouk, A.; Agouti, T. DM-MCDA: A Web-based Platform for Data Mining and Multiple Criteria Decision Analysis: A Case Study on Road Accident. *Soft. X.* **2019**, *10*, 100323. [CrossRef]
18. Ekmekcioğlu, Ö.; Koc, K.; Özger, M. Stakeholder Perceptions in Flood Risk Assessment: A Hybrid Fuzzy AHP-TOPSIS Approach for Istanbul, Turkey. *Int. J. Disast. Risk Re.* **2021**, *60*, 102327. [CrossRef]
19. Dai, B.; Li, D.; Zhang, L.; Liu, Y.; Zhang, Z.; Chen, S. Rock Mass Classification Method Based on Entropy Weight–TOPSIS–Grey Correlation Analysis. *Sustainability* **2022**, *14*, 10500. [CrossRef]
20. Raza, A.; Ali, M.U.; Ullah, U.; Fayaz, M.; Alvi, M.J.; Kallu, K.D.; Zafar, A.; Nengroo, S.H. Evaluation of a Sustainable Urban Transportation System in Terms of Traffic Congestion—A Case Study in Taxila, Pakistan. *Sustainability* **2022**, *14*, 12325. [CrossRef]
21. Zhao, Y.; Li, J.; Ying, X. Study on Risk of Long-Steep Downgrade Sections of Expressways Based on a Fuzzy Hierarchy Comprehensive Evaluation. *Appl. Sci.* **2022**, *12*, 5924. [CrossRef]
22. Ntafloukas, K.; McCrum, D.P.; Pasquale, L. A Cyber-Physical Risk Assessment Approach for Internet of Things Enabled Transportation Infrastructure. *Appl. Sci.* **2022**, *12*, 9241. [CrossRef]
23. Yari, M.; Monjezi, M.; Bagherpour, R. A Novel Investigation in Blasting Operation Management Using Decision Making Methods. *Rud. Geol. Naft. Zb.* **2014**, *29*, 69–79.
24. Yu, X.; Suntrayuth, S.; Su, J. A Comprehensive Evaluation Method for Industrial Sewage Treatment Projects Based on the Improved Entropy-TOPSIS. *Sustainability* **2020**, *12*, 6734. [CrossRef]
25. Yari, M.; Bagherpour, R.; Khoshouei, M.; Pedram, H. Investigating a Comprehensive Model for Evaluating Occupational and Environmental Risks of Dimensional Stone Mining. *Rud. Geol. Naft. Zb.* **2020**, *35*, 101–109. [CrossRef]
26. Hayaty, M.; Tavakoli Mohammadi, M.R.; Rezaei, A.; Shayestehfar, M.R. Risk Assessment and Ranking of Metals Using FDAHP and TOPSIS. *Mine Water Environ.* **2014**, *33*, 157–164. [CrossRef]
27. Yari, M.; Bagherpour, R.; Almasi, N. An Approach to the Evaluation and Classification of Dimensional Stone Quarries with an Emphasis on Safety Parameters. *Rud. Geol. Naft. Zb.* **2016**, *31*, 15–26. [CrossRef]
28. Lu, X.; Wang, Y.P.; Ziehn, T.; Dai, Y. An Efficient Method for Global Parameter Sensitivity Analysis and its Applications to the Australian Community Land Surface Model (CABLE). *Agr. Forest Meteorol.* **2013**, *182–183*, 292–303. [CrossRef]
29. Maxd; Morris. Factorial Sampling Plans for Preliminary Computational Experiments. *Technometrics* **1991**, *33*, 161–174. [CrossRef]
30. Cukier, R.I.; Levine, H.B.; Shuler, K.E. Nonlinear Sensitivity Analysis of Multiparameter Model Systems. *J Comput. Phys.* **1978**, *26*, 1–42. [CrossRef]
31. Sobol, I.M. Sensitivity Estimates for Nonlinear Mathematical Models. *Math. Mod Comput. Exp.* **1993**, *1*, 407–414.
32. Li, Y.; Huang, C.; Lu, L. Global Sensitivity Analysis of SEBS Model Parameters Based on EFAST Method. *Remote Sen. Tech. Appl.* **2014**, *29*, 719–726.
33. Saltelli, A.; Tarantola, S.; Chan, K. A Quantitative Model-Independent Method for Global Sensitivity Analysis of Model Output. *Technometrics* **1999**, *41*, 39–56. [CrossRef]
34. Broughton, J.; Knowles, J. Providing the Numerical Context for British Casualty Reduction Targets. *Safety Sci.* **2010**, *48*, 1134–1141. [CrossRef]
35. Hagenzieker, M.P.; Commandeur J., J.F.; Bijleveld, F.D. The history of Road Safety Research: A Quantitative Approach. *Transport. Res. F-Traffic.* **2014**, *25*, 150–162. [CrossRef]
36. Zhu, Y.; Liu, B.; Wang, S.; Yang, Z. Development of a FBG Stress Sensor for Geostress Measurement Using RSR Method in Deep Soft Fractured Rock Mass. *Appl. Sci.* **2022**, *12*, 1781. [CrossRef]
37. Hu, K.; Ge, H.; Li, H.; Xie, S.; Xu, S. Rate-Dependent Hysteresis Modeling and Displacement Tracking Control Based on Least-Squares SVM for Axially Pre-Compressed Macro-Fiber Composite Bimorph. *Materials* **2022**, *15*, 6480. [CrossRef]
38. Hu, L.; Zhang, C.; Zhao, X.; Liu, F.; Lyu, Y.; Xue, Y. A Method for Assessing the Risks of Freeway Segments with Combined Horizontal and Vertical Curves. *J. Transport Inform. Saf.* **2022**, *238*, 30–41.
39. Zhang, J.; Wang, W.; Li, T.; Luo, H. Global Sensitivity Analysis of Highway Beam Bridge Based on EFAST Method. *J. Civ. Eng. Manag.* **2020**, *37*, 51–56.
40. Jiang, L.; Cai, Q.; Zhang, Y.; Shi, H. Global parameter sensitivity analysis of passive system in nuclear power plant based on FAST. *J. Naval Univ. Eng.* **2018**, *30*, 65–70.
41. Tajnik, S.; Luin, B. Impact of Driver, Vehicle, and Environment on Rural Road Crash Rate. *Sustainability* **2022**, *14*, 15744. [CrossRef]
42. Ivajnšič, D.; Horvat, N.; Žiberna, I.; Kotnik, E.K.; Davidović, D. Revealing the Spatial Pattern of Weather-Related Road Traffic Crashes in Slovenia. *Appl. Sci.* **2021**, *11*, 6506. [CrossRef]