Load Characteristics-based Traffic Safety Risk Assessment

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Abstract. The weight of vehicles has a significant impact on traffic safety. Advanced vehicle weight measurement technologies, such as Dynamic Weighing (WIM), can use tire pressure sensors to obtain traffic and vehicle weight characteristics in a non-intrusive manner, providing the possibility for conducting traffic safety research that integrates vehicle weight. This study investigated the relationship between vehicle load characteristics (vehicle weight and gross vehicle ratio) and macro traffic safety indicators (average speed and standard deviation of speed). By analyzing the integrated data of traffic and meteorology, vehicle weight and the rate of large vehicles are significantly negatively correlated with the average speed, which means that the higher the rate of large vehicles, the lower the average speed. However, the correlations between vehicle weight, the rate of large vehicles and the standard deviation of speed are relatively weak. In addition, the correlation between meteorological factors and this average vehicle speed and the standard deviation of vehicle speed is extremely small. However, the model considering vehicle weight, the rate of large vehicles and axle load/number can well reflect the change in average speed. Studies show that in an intelligent and interconnected environment, traffic safety assessment should take vehicle weight and the rate of large vehicles as key indicators.

Keywords: Load Characteristics, Weight-in-Motion (WIM), Traffic Safety Risk Assessment, Intelligent Connected Environments.

1 Introduction

Load characteristics, such as vehicle weight, play a pivotal role in influencing traffic safety indicators. In an intelligent and interconnected environment, considering the load characteristics is extremely important for improving traffic safety and prolonging the service life of the road surface. However, the spatio-temporal traffic flow data obtained by traditional monitoring devices such as cameras usually do not contain vehicle weight information. Weight-in-Motion (WIM) technology offers a solution by measuring the traffic characteristics of operating vehicles without disrupting the traf-

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fic flow. WIM can control the error of monitoring parameters within 5% under different road and driving conditions, thus providing data support for vehicle weight estimation and safety assessment. Exploring the correlations of traffic factors, including load characteristics with safety indicators, is of vital importance for traffic safety assessment and optimization in the intelligent connected environment.

The safety of road traffic is influenced by a variety of interacting factors. Among these, the relationships between vehicle weight, the proportion of heavy vehicles, average speed, and speed standard deviation are of particular significance. A comprehensive exploration of these relationships is crucial for enhancing traffic safety levels, optimizing traffic management, and improving road design. From the perspective of vehicle characteristics impacting traffic safety, greater vehicle weight necessitates more energy to reach a certain speed, making acceleration more challenging. Liu pointed out that vehicle weight affects both power performance and braking performance, thereby influencing speed and safety. The higher the speed of a vehicle, the greater the risk of accidents; Moreover, the severity of an accident is related to changes in speeds before and after collisions [1]. Research by Zhang indicated that as the proportion of heavy vehicles increases (up to 30%), the capacity on single-lane urban highways without model conversion follows a specific quadratic function [2]. Zhou's study demonstrates that different mixing rates of heavy vehicles lead to individual operational differences among vehicles that result in mutual constraints; as traffic composition becomes increasingly complex, interference between vehicles intensifies—making the flow more sensitive to variations in individual speeds [3]. The lower speeds and reduced maneuverability associated with larger vehicles exacerbate discrepancies between macro-level flow speeds and micro-level individual vehicle speeds [4].

Furthermore, speed standard deviation reflects the degree of dispersion in vehicle speeds and serves as a key indicator for evaluating traffic safety. Russo BJ et al. argue that higher standard deviations indicate substantial differences in speeds, which can easily trigger rear-end collisions or overtaking accidents. The variance in speed (the square of standard deviation) shows a positive correlation with accident rates. Increased velocity variance leads to heightened incidence rates for accidents [5]. In segments where there is a high mixing rate between heavy and light vehicles—due to their respective differences in speed—the resulting large standard deviation typically elevates accident risks [6]. Existing research has established close connections among vehicle weight, proportions of heavy vehicles with average speed along with its standard deviation as indicators for safety. Vehicle weight influences power output and braking capability, thus impacting overall velocity and security; An increase in heavy vehicle proportions disrupts traffic flow leading to elevated accident rates; Additionally, average speed alongside its standard deviation exhibits significant correlations with incident frequency. However, current studies have limitations, such as insufficient consideration regarding multi-factor interactions [7]. It is particularly necessary to consider the impact of weather and road types on safety indicators [8,9]. In addition, it is essential to strengthen comprehensive multi-factor research using advanced technical methods, construct improved models, and obtain precise data. These efforts can provide the necessary scientific basis for effective traffic management strategies and road design improvements aimed at significantly enhancing road safety standards [10,11].

The study aims to address these gaps by investigating the relationship between traffic elements that integrate vehicle load characteristics and traffic safety risk indicators. Through the analysis of comprehensive data integrating traffic, load and meteorology, the influence relationship law of traffic safety risk indicators under the action of a single element and the combined action of multiple elements is explored. The results of this study can provide valuable insights into traffic management and road design in an intelligent and interconnected environment.

2 Methodology

2.1 Correlation Analysis Based on Spearman's Rank Correlation Coefficient

Based on the fusion of WIM data and meteorological data, the data is divided into traffic element information at different times according to a time granularity of 15 minutes and a speed granularity of 5 km/h. Traffic safety risk indicators studied in this research include average speed and standard deviation of speed. To analyze the correlation between traffic elements and traffic safety risk indicators, the relationship between large vehicle rate and traffic safety risk indicators is studied. Based on it, the Spearman rank correlation coefficient, a commonly used statistical indicator for evaluating the correlation degree between ranked variables, is selected to calculate the linear relationship between vehicle weight and traffic element (including time, lane, the leading and following vehicle speed, length and axle number, time headway, day of the week, average temperature, weather condition, vehicle type). Based on the Spearman correlation coefficient calculation results, the main influencing factors of vehicle weight estimation can be determined. Grouping based on the main influencing factors for vehicle weight estimation can improve accuracy. The Spearman rank correlation coefficient can be calculated by using formula(1). Formula (1) provides a measure of the strength and direction of the monotonic relationship between two variables. In this study, it is used to assess how changes in vehicle weight and other traffic elements are related to changes in average speed and speed standard deviation.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{1}$$

Where ρ is the Spearman rank correlation coefficient, d_i is the difference between the ranks of the corresponding variables, n is the number of observations.

2.2 Goodness-of-fit Analysis Between Load Characteristics and Traffic Safety

The macro-traffic volume can be divided according to the time granularity of 15 minutes, and the characteristics of traffic flow elements within each 15-minute time interval can be calculated. The average speed and speed standard deviation are important indicators for measuring macro-traffic flow safety. Set time period and traffic volume as a fixed input variable. Propose 5 different control variables (include ①weight and number of each axle type vehicle; ②large vehicle rate; ③average vehicle weight; ④average vehicle weight, large-scale vehicles occupation rate, weight and quantity of each axle type vehicle; ⑤average vehicle weight, large vehicle rate, weight and number of each axle type vehicle, weather conditions.) to predict the average vehicle speed and speed standard deviation. R-squared (R^2) and RMSE index were selected to verify the effect of the large-scale vehicles occupation rate on traffic safety indicators. R^2 is used to measure the degree of difference between the observed data and the expected data, as shown in the formula (2). Meanwhile, RMAE can reflect the predictive performance of the model more sensitively, as shown in the formula (3). RMSE is calculated by taking the square root of the average of the squared differences between each predicted value and its corresponding actual value.

$$R^2 = \sum_{i=1}^{n} \frac{(y_i - \bar{y}_i)^2}{\bar{y}_i} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2}{n}} \tag{3}$$

3 The Relationship Between Traffic Elements and Traffic Safety

3.1 The Relationship Between Load Characteristics and Traffic Safety Risk Indicators

Figures 1 and Figure 2 analyze the influence relationships between the rate of large vehicles and vehicle speed, as well as the standard deviation of the rate of large vehicles and vehicle speed, respectively. Based on them, Table 1. presents the relationship between the large vehicle rate and traffic safety risk indicators, including average speed and standard deviation of speed. The R^2 value of the relationship function between large vehicle rate and average speed is 0.691, which indicates that the large vehicle rate can explain 69.1% of the variation in average speed. The RMSE of 7.154 provides a measure of the differences between the values predicted by the model and the values actually observed. The fitting curve in Figure 1 has a good characterization effect. However, The R^2 value of the relationship function between large vehicle rate and standard deviation of speed is 0.045, suggesting that only 4.5% of the variation in speed standard deviation can be explained by the large vehicle rate. Therefore, the fitted function expression and the fitting curve in Figure 2 have a poor representation effect to reflect the relationship law between the large vehicle rate and the standard deviation of speed.

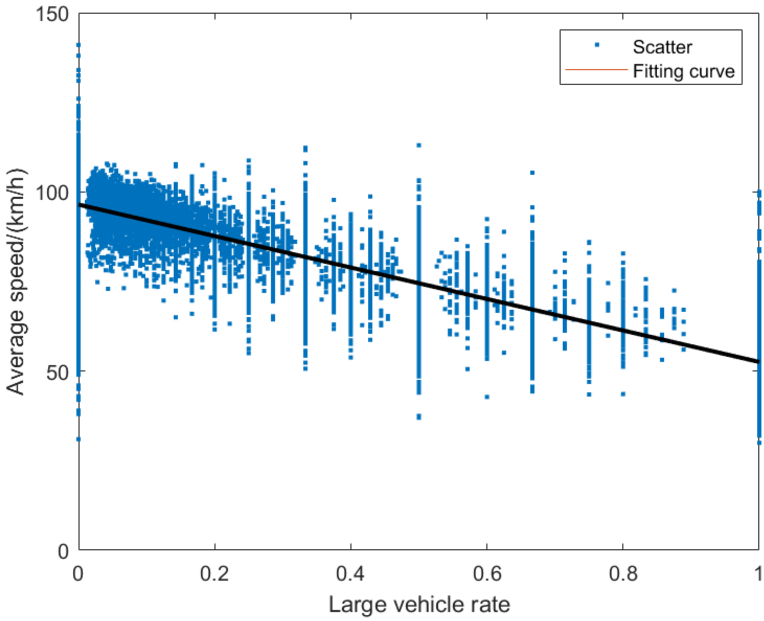

Fig. 1. The relationship between large vehicle rate and average speed.

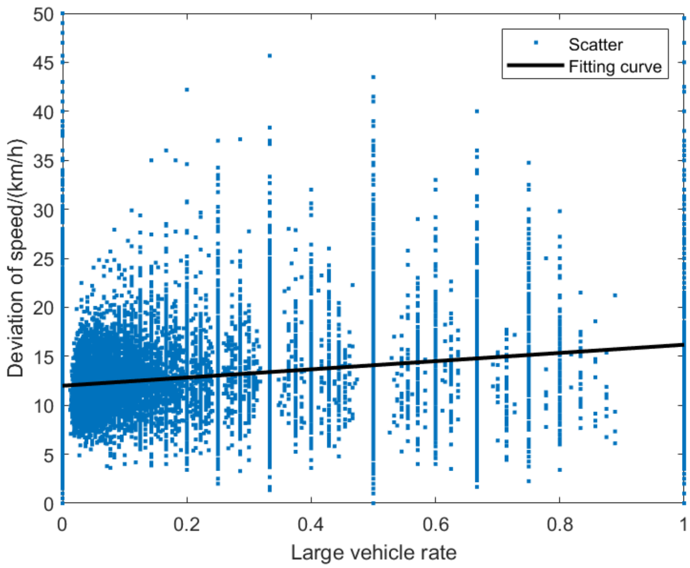

Fig. 2. The relationship between large vehicle rate and standard deviation of speed.

Table 1. The relationship between large vehicle rate and traffic safety risk indicators.

	Relational function expression	R^2	RMSE
Large vehicle rate-Average speed	V_mean = -43.910*w + 96.460	0.691	7.154
Large vehicle rate-Standard deviation of speed	V_std = 4.186*w + 11.990	0.045	4.702

Where w is large vehicle rate, V_mean is average speed, V_std is standard deviation of speed.

Table 2 presents the correlation coefficients between traffic elements and average speed. Vehicle weight, large vehicle rate and 2-axle vehicles demonstrate strong associations with vehicle weight, with coefficients of -0.784, -0.742 and 0.668, respectively. A strong negative correlation is observed between the loading characteristics and average speed, which implies that a higher proportion of large vehicles in traffic is associated with lower average speeds. This is likely due to the slower operating speeds of large vehicles compared to lighter ones.

Table 2. The correlation coefficient between traffic elements and average speed.

Vehicle traffic characteristics	Time	Vehicle number	2-axle vehicle number	3-axle vehicle number	4-axle vehicle number	5-axle vehicle number
Correlation coefficient	0.243	0.607	0.668	-0.221	-0.284	-0.156
Vehicle traffic characteristics	6-axle vehicle number	2-axle vehicle weight	3-axle vehicle weight	4-axle vehicle weight	5-axle vehicle weight	6-axle vehicle weight
Correlation coefficient	-0.394	-0.214	0.076	-0.023	-0.041	-0.017
Vehicle traffic characteristics	Vehicle weight	large vehicle rate	Day of the week	Average temperature	Weather condition	Wind condition
Correlation coefficient	-0.784	-0.742	-0.030	0.196	0.009	0.038

Table 3 shows the correlations between traffic elements and speed standard deviation. Vehicle weight and large vehicle rate demonstrate strong associations with vehicle weight, with coefficients of 0.209 and 0.191, respectively. Meanwhile, most traffic elements have weak correlations with the standard deviation of speed. Environmental factors show minimal correlations with average speed and standard deviation of speed.

Table 3. Correlation coefficient between traffic elements and standard deviation of speed.

Vehicle traffic characteristics	Time	Vehicle number	2-axle vehicle number	3-axle vehicle number	4-axle vehicle number	5-axle vehicle number
Correlation coefficient	0.016	-0.135	-0.146	-0.007	0.075	0.054
Vehicle traffic characteristics	6-axle vehicle number	2-axle vehicle weight	3-axle vehicle weight	4-axle vehicle weight	5-axle vehicle weight	6-axle vehicle weight
Correlation coefficient	0.151	0.007	0.013	0.038	0.038	0.067
Vehicle traffic characteristics	Vehicle weight	large vehicle rate	Day of the week	Average temperature	Weather condition	Wind condition
Correlation coefficient	0.209	0.191	-0.021	-0.048	0.028	0.015

From the traffic safety perspective, large vehicles significantly impact traffic flow. Their slower speeds and potential to cause speed differentials may increase accident risks. Effective traffic management strategies targeting large vehicles could enhance safety. The negative correlation between vehicle number and speed standard deviation suggests speed differences are reduced in congested traffic, but congestion can lead to risky driving behaviors. While environmental factors show weak correlations in this analysis, extreme weather conditions can still significantly impact road safety. Proactive measures to monitor and respond to adverse weather are essential. Understanding these correlations helps identify critical factors influencing traffic flow and safety. Focusing on large vehicle management and congestion mitigation, along with preparing for environmental challenges, can lead to safer and more efficient traffic systems.

3.2 Multivariate Fitting Analysis of Traffic Elements and Safety Indicators

Multivariate Fitting was used to explore the linear relationship between statistical traffic safety indicators and traffic elements. Table 4 shows the goodness of fit between traffic elements and traffic safety risk indicators (average speed and standard deviation of speed) using different methods. Methods 1-5 show progressively improving fits for explaining average speed variations, with Method 5 providing the best balance. Methods 4 and 5 demonstrate the best performance in terms of R^2 and RMSE for average speed. However, the explanatory power for speed standard deviation remains relatively low across all methods, with only slight improvements observed. The results show that while the inclusion of additional variables enhances the model's ability to explain average speed variations, further research and refinement are needed to understand better and model the factors influencing speed standard deviation.

Table 4. The goodness of fit between traffic elements and traffic safety risk indicators.

Method	The Input Variables	Average Speed/ (km/h)		standard deviation of speed/ (km/h)	
		R^2	RMSE	R^2	RMSE
1	Weight and number of each axle type vehicle, time, traffic volume.	0.695	5.630	0.083	2.840
2	Large-scale vehicles occupation rate, time, traffic volume.	0.717	6.840	0.057	4.670
3	Average vehicle weight, time, traffic volume.	0.748	6.454	0.084	4.603
4	Average vehicle weight, large vehicle rate, weight and number of each axle type vehicle, time, traffic volume.	0.829	4.330	0.109	2.810
5	Average vehicle weight, large vehicle rate, weight and number of each axle type vehicle, weather conditions, time, traffic volume.	0.834	4.310	0.119	2.820

4 Conclusion

This study mainly investigates the relationship between key traffic elements such as vehicle weight and large vehicle occupancy rate and traffic safety risk indicators such as average vehicle speed and vehicle speed standard difference. The following conclusions can be drawn:

1.The average vehicle weight and the rate of large vehicles are significantly negatively correlated with the average vehicle speed, with R^2 values of -0.784 and -0.742, respectively. The result indicates that load characteristics have a considerable influence on average speed. It is likely caused by the fact that the running speed of large vehicles is slower than that of small vehicles. Although the relationship between average vehicle weight, large vehicle rate and average vehicle speed is significant, the explanatory power of average vehicle weight and large vehicle rate for the standard deviation of speed is limited (R^2 is 0.209 and 0.191, respectively).

2.Environmental factors exhibit very weak correlations with average speed and speed standard deviation, suggesting that their influence on these safety indicators is relatively small within the scope of this study.

3. The number of variables is positively correlated with the degree of fit. Incorporating sufficient traffic elements can improve the characterization performance of the fitting model for average speed and the standard deviation of vehicle speed.

To sum up, this study emphasizes the significant impact of vehicle weight and large vehicle ratio on traffic safety risk indicators. Implementing effective traffic management strategies for the operation of large vehicles can reduce speed differences and potential accident risks, thereby enhancing traffic safety. Future research should focus on the inclusion of precise meteorological data, spatiotemporal continuous data, and data from different types of highways and explore advanced traffic safety risk assessment methods that integrate multiple factors. These efforts will contribute to the development of safer and more efficient transportation systems in an intelligent connected environment. Future research should further integrate precise meteorological elements, continuous spatiotemporal data, and data from different types of highways, with the aim of exploring the relationship between multivariate and safety indicators and improving the accuracy of traffic safety assessment methods.

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