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Research Article

An AHP-ME-Based Vehicle Crash Prediction Model considering Driver Intention and Real-Time Traffic/Road Condition

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Although numerous studies have attempted to use vehicle motion data for real-time vehicle crash prediction, many driver behavior and road/environment factors (e.g., driving intention and pavement condition) have not been considered. In order to cope with increased complexity and extent crash risk assessment with the consideration of factors like driving intention and pavement condition, this paper (a) combines driver intention, vehicle motion, and dynamic traffic environment into the assessment of the conflict risk in real time, (b) establishes a hierarchical analysis model for quantitatively describing driving safety based on an Analytic Hierarchy Process (AHP), and (c) applies a Matter Element (ME) Model to take multiple factors, which are heterogeneous in terms of nature of analysis (quantitative or qualitative) and measure units, into account, and provide a comprehensive evaluation of vehicle crash risk. Finally, a set of simulation cases are used to compare the detection efficiency of the proposed method with ANN and SVM for vehicle collision. The example analysis shows that the proposed AHP-ME model can more accurately predict the collision risk of vehicles. Moreover, the proposed AHP-ME model provides an effective solution to unify multi-factors (driver intention, vehicle motion, and dynamic traffic environment) into an integrated decision-making framework.

1. Introduction

Advanced Driver Assistance System (ADAS) can be used to identify dangerous scenarios and provide timely warning and reaction in case of emergency, where a driver makes a mistake or may not be consciously aware of such a mistake. The ADAS uses advanced sensor and information technologies to enhance driver's awareness to road, traffic, and safety. Such information is synthesized by the system to identify safety hazard and potential risks in real time.

Crash risk assessment models are of vital importance for ADAS to provide better prediction and analysis of driving safety in emergency. Jin et al. analyzed the reliability of the uncertain fractional-order dynamic system with a state constraint , the sensitivity analysis is also presented for the numerical examples [1]. Xu et al. proposed a novel non-BP learning algorithm based on the differential evolution algorithm is proposed, by fully incorporating the feedback information from evolving population and individuals, the proposed algorithm significantly outperforms the other ten state-of-the-art non-BP algorithms and BP in terms of the classification accuracy [2]. Jin et al. proposed a new competing failure model for a fractional-order RC circuit system that is presented and analyzed for reliability, which is proved to be of practical importance by numerical simulations [3]. Jin et al. investigated the optimal control problem of the uncertain second-order circuit based on first hitting criteria; analytic expressions of the optimal control for the reliability index model are obtained [4]. However, a literature review carried out for this study indicates that few, existing crash risk assessment models developed have taken driver behavior into consideration, although it has been long recognized as one of the most important factors that should be considered in vehicle crash risk assessment. In this paper, the Analytical

Hierarchical Process (AHP) and a Matter Element (ME) model are combined to establish a vehicle collision risk situation assessment model. On one hand, our proposed method constructs the system of vehicle crash risk assessment by a hierarchical model, which could consider more driving safety related factors (driver intention, vehicle motion, and dynamic traffic environment) into a decision-making framework. On the other hand, the proposed AHP-ME model can effectively quantify the vehicle crash risk.

The main contribution of this paper is that our proposed hierarchical analytical model can comprehensively consider a set of driving safety related factors, both quantitative (e.g., vehicle motion and road surface [5]) and qualitative (e.g., driving intention, driver fatigue, and weather [6]). It should be noted that a significant heterogeneity exists in the data used to develop the proposed hierarchical analytical model, when integrating all these factors to evaluate crash risk. In order to cope with this heterogeneity and the increased complexity, an AHP-ME model is proposed to extend crash risk assessment with the consideration of multi-factors. The proposed hierarchical analysis model combines driver intention, vehicle motion, and dynamic traffic environment into the assessment of the crash risk in real time, which can quantitatively describe driving safety based on the Analytic Hierarchy Process and apply a Matter Element Model to evaluate vehicle crash risk. Finally, a group of simulation cases are used to compare the efficiency of crash detection of the proposed AHP-ME model with that of a classic Safety Distance Model. The simulation results show that the AHP-ME model proposed in this paper can reflect the current driving safety conditions more realistically, to effectively predict vehicle collisions. The research results can provide a basis for traffic safety analysis.

This paper is organized as follows: Section "Literature review" presents a review to research in the field of safety distance and TTC (time to collision) model, the critical zone model, and the risk identification model based on multiple information fusion. In Section "Methodology", the proposed AHP-ME model and its application in vehicle crash risk assessment are described. Then, a group of simulation cases are used to analyze the efficiency of crash detection of the proposed AHP-ME model with that of the Safety Distance Model in Section "Evaluation results". Finally, Section "Conclusions and recommendations" presents the conclusions and recommendations of this study.

2. Literature Review

This review provides an examination to the research development in the field of safety distance and TTC (time to collision) model, the critical zone model, and the risk identification model based on multiple information fusion, which is subsequently detailed in the following sections, respectively.

2.1. Safety Distance Model. Approaching vehicles should be maintained a safety distance between the front vehicle and behind vehicle, which can effectively prevent the collision accident between the two vehicles [7, 8].

Safety distance model can be divided into workshop safety distance model and headway safety distance model. Hou et al. improved the shortcomings of the original workshop distance model by calibrating the safety distance model based on a group of driving test, the improved model can be effectively applied in vehicle active collision avoidance system and reflected the driver characteristics [7, 9]. Based on the established safe distance model of following and changing routes, the results show that the actual collision avoidance process of the vehicle is well simulated in the virtual environment, and the controlled vehicle is in an active safe driving state [10]. He used millimeter wave radar to set up vehicle safety distance in vehicle collision avoidance system, which can shorten the safety distance between vehicles, guarantee vehicles safety, improve the highway transportation efficiency, and promote the rapid development of the economy. This study finds that the influence of the workshop safety distance are the main factors affecting the driving speed, the driver's reaction ability, road conditions, weather, load, and the frequency of vehicle braking [11]. Jamson et al. based on the safety distance between vehicles, the driver driving simulator, analyzed the safe driving of the drivers of time, thus established the early warning scheme is different, to ensure the safety of the travelling [12].

Headway refers to the ratio of distance and the vehicle speed; based on safety distance model, the author established a relatively small follow driving velocity; the characteristics and the distance between the front vehicle and vehicle speed have a linear relation [13, 14]. Tian et al. analyzed the design requirements of automobile rear end collision warning system, based on safety distance algorithm, combined with the kinematic analysis of automobile braking process, established an improved headway and the safe distance of vehicle dynamics mathematical model based on [15]. Tang proposed a safety distance model based on brake process and based on the safety distance model from the workshop, established the calculation model considering the safety distance of vehicle motion state [13]. Sweden used the headway of safety on the highway which is evaluated and pointed out the shortcomings as well as the improvement of safety distance model [16]. Ayres et al. focused on the safety distance model of the time headway based on, the method for extracting the representative headway data from a large number of the actual highway in the study, after applied to traffic safety guide [17].

2.2. Critical Zone Model. The safety distance model vehicles from the workshop or workshop based on distance, conflict risk identification method have low accuracy, the key parameter is not easy to obtain, on the driver's subjective factors into the problems such as inadequate. Risk identification vehicle conflict therefore safety distance model is mainly suitable for single round, not suitable for longitudinal and transverse. At present, for the increasingly complex road environment, a full range of automotive collision risk assessment has become a research trend.

In order to improve the inadequate existed in safety distance model, someone has put forward the risk identification method of vehicle based on the definition of conflict area, this method can consider the vehicle around the degree of conflict adjacent vehicles, pedestrians, obstacles, and itself. Guo et al. proposed a critical conflict area and calculate the critical radius based on vehicle motion status, the motion characteristics, and risk perception of regional conflict vehicle closely is more practical and more universal [18, 19].

2.3. Risk Identification Model Based on Multi-Information Fusion. All the above two methods not consider the driving intent which impacts on traffic safety status, in the actual road traffic, the driver intention has great influence on the driving safety status of automobile. According to the statistics, driver is the main cause of road traffic accidents, these accidents account for more than 80% of the total [20]. Germany Daimler-Benz company points out in his study, if the driver gets the warning before 0.5 seconds when the accident happens, 60% rear end accidents can be avoided, if can add a second time 90% rear end accidents can be avoided [21]. The Swedish scholar Sonja E. Forward analyzed the reasons causing the driver illegal operations from the mechanism, found that even under traffic environment constraints, the driver still tends to find space to achieve the purpose of speed, and this tendency in the main street is more than the main road [22]. Ren through a questionnaire and mathematical statistics to get the driver's reaction time data, such as depth perception, attention and concentration distribution, the driver specific reaction time by driving simulation test, the reaction time model is established by linear regression method, results show that the credibility of this model to express the responding time of the driver and the factor has a linear relationship with up to 95%, the effective rate of the classification which is used to predict is up to 79% [23].

Therefore, the "human - vehicle - road" multi-information identification car conflict risk technology is put forward, such as neural network method, AHP, fuzzy evaluation method, the cellular automata method, and multiple information fusion technology, in this regard, at home and abroad have carried out relevant research. Shi et al. used fuzzy neural network to identify and analyze driver proficiency, fatigue, comprehensive active safety, and quantitatively analyze the influencing factors of active driving safety [24]. Li et al. based on neural network evaluation method, considering the influence of driver, vehicle, environment and management factors on vehicle safety state, established evaluation system of vehicle safety state, provides a new method for vehicle risk identification [25]. Song et al. made safety assessment using analytic hierarchy process on the machine running safety, and through the locomotive rash advance signal as an example, discussed that the feasibility of the application of analytic hierarchy process as a safety evaluation method is convenient and effective to the locomotive operation safety evaluation [26]. Liu et al. made safety assessment on the safety conditions of freeway traffic accident using cellular automata [27]. Liu et al. made the comprehensive detection for the driving state using multi-source information fusion technology, which construct traffic safety rules, and make detection, analysis, and judgment on vehicle real-time risk and potentially dangerous, obtain the collision reliable warning, the reaction time, relative distance, relative velocity can be optimized control, so as to avoid vehicle collision accident [28]. Liao et al. proposed a dynamic object tracking algorithm based on multi-sensor information fusion to realize the collision avoidance system of information acquisition, established the automobile environment state features model, on the basis of this, using the fuzzy integral information fusion method, determine the safe operation mode should be adopted, implement active safety collision avoidance decision-making [29]. Zhou makes a fusion of radar and infrared sensors for automotive anti-collision system based on multi-sensor fusion technology [30]. Tian et al. established driving safety evaluation index system based on the principle of fuzzy comprehensive evaluation [31]. Chang et al. analyzed the driver fatigue driving safety process, and propose a fuzzy evaluation method to study the collision warning system [32]. Toledo-Moreo and Zamora-Izquierdo take research on collision time and distance in the traffic safety incidents based on the information fusion method [33]. Lu proposed a crash risk prediction method based on Kalman Filter and Bayesian network; it can sense the environment around the subject vehicle [34]. Kaempchen et al. used situation assessment of the braking time collision process of the emergency brake is improved, to make it better in collision avoidance [35].

Although the studies reviewed above integrates the "driver-vehicle-road" multiple heterogeneous data to evaluate the vehicle crash risk, the key technology of how to eliminate the heterogeneity results from the related factors is still an unresolved problem in the current study. Aiming at the deficiency in the existed literature, a proposed method in this paper combines the Matter Element analysis method and the Analytic Hierarchy Process, considering the impact of driver, vehicle motion, and road environment factors on driving safety status.

3. Methodology

3.1. Traffic Conflict Risk Evaluation Index System. At present, the research for the dynamic state of vehicle safety evaluation system has not yet formed a unified standard. American scholars TREAT's research results show that in the road traffic accident, the effect of people, vehicles, and road factors on the vehicle safety status is interrelated, the relationship between the statistical results as follows: person, vehicle, road, vehicle, vehicle, vehicle, road in road accident cause ratio were 57%, 2%, 3%, 2%, 37%, 1%, and 37% [10]. According to the ministry of public security traffic management bureau in 2012 national road traffic accident statistics show that the state of vehicle safety influence factors, the main driver factors, followed by the vehicle factors, in addition to environmental factors and management factors also cannot be ignored. According to the above information, this article selects the road vehicle conflict mainly involved in the accident to the driver factors (state of fatigue, driving behavior and intentions, etc.), vehicle running status (speed, shape, etc.), and road traffic environment (weather, road, obstacles, etc.). These three factors establish traffic conflict risk evaluation index system, as shown in Figure 1.

3.2. Evaluation Index. Vehicle traffic safety status identification and evaluation should follow the principles of comprehensive, independent and easy to quantify and operate, aspires to direct effects and indirect effects, can more objectively reflect the driver state, vehicle running status, and road traffic environment on the influence of road safety situation [13]. In view of this, based on the literature [13, 18], as well as six indexes in Figure 1, the road safety situation characteristic indexes and the evaluation grade division standard are explained. This paper is divided into four grades for the vehicle safety status, and determines the value range for the characteristics of each level, as shown in Table 1.

3.3. Construction of AHP-ME Evaluation Model. In this section, an AHP-ME model is introduced into vehicle crash risk evaluation. A relative integrated evaluating index which combines with the condition and characteristics in vehicle collision accidents and their values are considered in this model. The proposed model aims to exactly evaluate the comprehensive level of driving safety.

3.3.1. Matter Element Analysis Model. Matter Element analysis theory was created by Wen Cai, a Chinese professor. It is a new subject that between mathematics and experimental science and its study focused on the contradiction problems of real world. Things have a variety of features and every attribute has a corresponding value. Set N as the name of things, and its value is named V about feature of C. $R = \{N, C, V\}$ is named matter element. If things have N attributes, then it can be expressed as follows:

$$R = \begin{bmatrix} N & C_1 & V_1 \\ C_2 & V_2 & \\ \vdots & \vdots & \\ C_n & V_n & \end{bmatrix} = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{bmatrix}. \quad (1)$$

R is named as N dimensional matter-element. The concept of matter-element provides a new way for solving the problem that how to judge the extent things belongs to a set according to the value about a feature. Correlation function makes identification more refined. By using extension set and correlation function, a new way can be set up to identify ambiguous things [11]. At present, matter-element has been widely used in many fields.

A Matter Element Model is built based on a set of Classical field, controlled field, and evaluated matter element, which are defined as follows:

Definition 1. Classical field N_j represent the j th level evaluation index, it can be described as follows:

$$R_j = \left(N_j, \mathbf{C}_j, \mathbf{X}_j\right) = \begin{bmatrix} N_j & c_1 & \left(a_{j1}, b_{j1}\right) \\ & c_2 & \left(a_{j2}, b_{j2}\right) \\ & \vdots & \vdots \\ & c_n & \left(a_{jn}, b_{jn}\right) \end{bmatrix}, \quad (2)$$

where $N_j\,(j = 1, 2, \ldots, n)$ means jth level $C_j\,(j = 1, 2, \ldots, n)$ is the subindicator, represents the feature of corresponding evaluation hierarchy. $X_{ji} = (a_{ji}, b_{ji})$ represents the attribute value of c_{ji} at the jth level evaluation index.

Definition 2. Controlled filed describes the value range of all attribute, it can be described as follows:

$$R_p = \left(P_j, \mathbf{C}_i, \mathbf{X}_p\right) = \begin{bmatrix} P & c_1 & \left(a_{p1}, b_{p1}\right) \\ & c_2 & \left(a_{p2}, b_{p2}\right) \\ & \vdots & \vdots \\ & c_n & \left(a_{pn}, b_{pn}\right) \end{bmatrix}, \quad (3)$$

where P_j represents all of evaluation hierarchy, and $X_{pi} = (a_{pi}, b_{pi})$ represents the attribute value of c_i at the every level evaluation index.

Definition 3. For the scheme to be rated, all subindicator can be expressed by R_0, it can be described as follows:

$$R_0 = \begin{bmatrix} N_0 & C_1 & x_{01} \\ & C_2 & x_{02} \\ & \vdots & \vdots \\ & C_n & x_{0n} \end{bmatrix}, \quad (4)$$

where R_0 represent the matter element to be rated, N_0 means the scheme to be rated.

3.3.2. Attribute Weight Determining Based on Analytic Hierarchy Process (AHP). In this section, the Analytic Hierarchy Process (AHP) is applied to determine the weight of attributes representing each of their corresponding effect on the driving safety. Related factors (driver behavior, vehicle motion state, weather, road surface, and driver fatigue) are comprehensively considered and evaluated by practiced driver, and the investigated results are recorded through a group of questionnaires.

Analytic Hierarchy Process (AHP) is a decision-making method that had been developed and designed to solve complex multi-criteria decision problems [36]. AHP requires the decision maker to provide judgment about the relative importance of each criterion, and then to specify a preference for each decision alternative using each criterion. AHP allows better, easier, and more efficient identification of selection criteria, their weighting, and analysis. AHP allows a logical mixture of data, which could be quantitative, qualitative, experience, insight, and intuition in its algorithmic framework. It enables decision makers to find the weight of

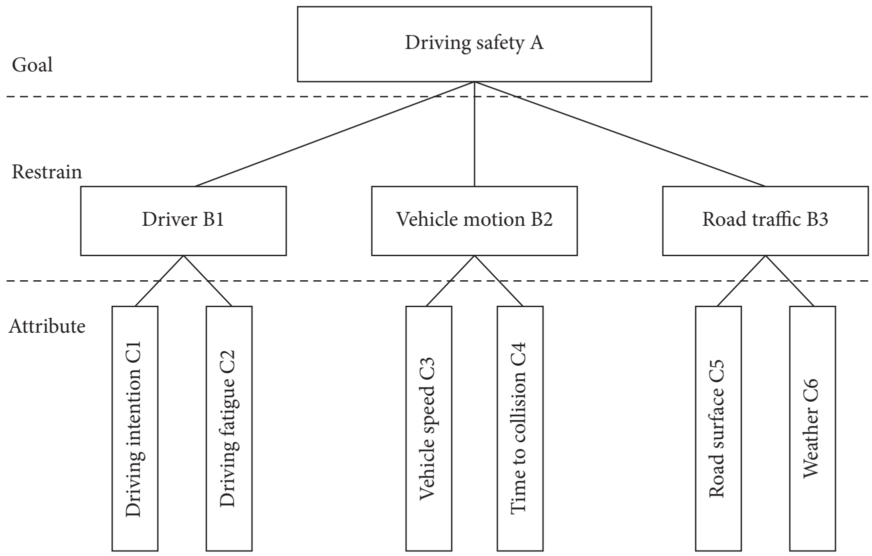

Figure 1: Architecture of collision risk assessment.

Table 1: Index of driving safety related factors.

Attribute	Index	Safety grade			
		Dangerous (grade 1)	Less dangerous (grade 2)	Less safe (grade 3)	Safe (grade 4)
Traffic environment	Time to collision (s)	**(1, 2)**	**(2, 3)**	**(3, 4)**	**(4, 5)**
	speed (km/h)	**(80, 100)**	**(60, 80)**	**(40, 60)**	**(20, 40)**
	Visibility (m)	**(0, 50)**	**(50, 100)**	**(100, 150)**	**(150, 200)**
	Pavement slippery (adhesion coefficient)	**(0.1, 0.3)**	**(0.3, 0.5)**	**(0.5, 0.7)**	**(0.7, 0.9)**
Driver	Driving intention	Accelerate	Constant speed	Lane change	Decelerate
	Driver fatigue	**(0, 3)**	**(3, 6)**	**(6, 9)**	**(9, 12)**

each criterion, as shown in Figure 2. In order to get the decision, we need the following steps:

(1) Identify the alternatives, the criteria and subcriteria. Subcriteria may not be available for all criteria, which means that only criteria should be identified.

(2) Building the pairwise comparisons by establishing the priorities for the available criteria and then compare between each pair based on the most important criterion. Then, constructing a matrix of the pairwise comparison rating to determine the priorities for all criteria.

(3) After constructing the pairwise comparison matrix, then it must calculate the priority of each criterion in terms of its contribution to the overall goal of selecting the best among the alternatives. This step is called synthetization. In order to achieve a good approximation result that should be followed, there are three steps as follows:

  (1) Finding the sum of each column in the matrix.

  (2) Dividing each element in the pairwise comparison matrix by its column total. The resulting matrix refers as Normalized pairwise comparison matrix.

  (3) Compute the average of elements in each row of the normalized pairwise comparison matrix. This average shows the priorities for each criterion.

Finally, deciding whether the pairwise comparison is consistence or not. This operation is called consistency. AHP provides a measurement of consistency for pairwise comparisons by computing the Consistency Ratio. If the result of the Consistency Ratio is greater than 0.1, it indicates an inconsistency in the pairwise comparison. Therefore, if the Consistency Ratio is 0.1 or less, the value of the consistency of the pairwise comparison is considered as reasonable. The steps are as follows:

(1) Multiply each value in the first column of the pairwise comparison matrix by the priority of the first item, multiply each value in the second column of the pairwise comparison matrix by the priority of the second item, and so on. Then, sum the values across the rows to obtain a vector values which is called "weight sum". Compute the average values of the weight sum by priority for each criterion. If the eigenvalue and eigenvector of the attribute judgment matrix are λ_i and w_i, set:

$$\check{y}_i = \frac{y_i}{1/n\sum_1^n y_i}, \quad i = 1,2\ldots n,$$
$$W_i = \frac{\sum_1^n \check{y}_i}{n}. \tag{5}$$

where y_i is the elements before normalization, $\check{y}_i$ is the elements after normalization, n is the number of indicators, W_i is Weight.

Then, the biggest characteristic root for pairwise comparison matrix is:

$$\lambda_{\max} = \sum \frac{(\mathrm{BW})_i}{nW_i}. \tag{6}$$

(2) Compute the Consistency Index CI by the following formulas:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1}. \tag{7}$$

(3) Compute the Consistency Ratio CR by the following formulas:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \tag{8}$$

where RI is the consistency index of a random generated pairwise comparison matrix. The value for RI depends on the number of items being compared, as shown in Table 2:

3.3.3. Dependent function. Dependent function is used to determine the dependent degree of the evaluated matter to the certain evaluation characteristics.

The distance in AHP-ME theory is different from classical mathematics. Suppose that $x_0 \in X(a,b)$ is any point, and $\rho(x_0, X)$ represent the distance between point x_0 and interval X, which can be described as follows:

$$\rho(x_0, X) = \left|x_0 - \frac{a+b}{2}\right| - 0.5(b-a) = \begin{cases} a - x_0, & x_0 \leq \dfrac{a+b}{2}, \\ x_0 - b, & x_0 \leq \dfrac{a+b}{2}. \end{cases} \tag{9}$$

The dependent function $K_j(x_i)$ of x_i regarding intervals X_{ji} and X_{pi} can be described as follows:

$$K_j(x_i) = \begin{cases} \dfrac{\rho(x_{0i}, X_{ji})}{\rho(x_{0i}, X_{pi}) - \rho(x_{0i}, X_{ji})}, & x_{0i} \in X_{ji}, \\ \dfrac{-\rho(x_{0i}, X_{ji})}{|X_{ji}|}, & x_{0i} \in X_{ji}, \end{cases} \tag{10}$$

where the $\rho(x_{0i}, X_{ji})$ is the distance between point x_{0i} and interval X_{ji}, and the $\rho(x_{0i}, X_{pi})$ is the distance between point x_{0i} and interval X_{pi}.

Thus, the dependent degree can be calculated as follows:

$$K_j(N_0) = \sum_{i=1}^n a_i K_j(x_i). \tag{11}$$

Suppose the class level of evaluation object is j (j = 1,2, . . ., m). Where a_i represent the weight of each attribute, $K_j(N_0)$ is dependent degree of N_0 belonging to the jth level. If $K_j(N_0) = \max K_i(N_0)(i = 1, 2, \ldots, m)$, then N_0 belongs to the jth level.

3.4. Evaluation of Vehicle Crash Risk. If $K_{j0} = \mathrm{Max}K_j(N_0)$, then N_0 belongs to j0th. Direct using the standard of the level of risk which has made directly, $K_j(x_i)$ as the foundation, the correlation degree is used to identify the level, overcoming the different index range conversion. In addition, the size of the correlation also reflects to a review of the state of vehicle safety degree of a level standard; the greater the numerical, in line with the higher degree; for all the j0, $K_j(x_i) \leq 0$, said the state of vehicle safety has not in the level divided, should be to identify again.

4. Evaluation Results

Based on vehicle crash risk evaluation indices, certain traffic scenarios can be regarded as an evaluated matter element, thus, each vehicle running state evaluation indices can be expressed with the quantitative values.

In this section, a case of vehicle driving safety status is evaluated assumed under the environment of vehicular cyber physical system. Combined with the related factors presented in Table 1, it explains the matter-element analysis model on the application of the safety evaluation of road traffic vehicle driving. Subject vehicle in running state can be detected by infrared/millimeter wave radar and the vehicles workshop interval, and visibility, tire-road friction coefficient can be obtained by indirect wheel speed sensor, the vehicle speed can be observed on the dashboard. We choose a traffic scene and study the driving safety evaluation under different driving intention (driving at constant speed, taking acceleration, taking deceleration, and lane change). In this case study, all the related factors are assumed to be detected by vehicular cyber physical system, and the corresponding value are shown in Table 3.

With the equations described in section “Dependent function”, the dependent function can be gained eventually. Each evaluation indices weight is gained based on analytic hierarchical process method, and the results are shown in Table 4.

Considering each evaluation indices weight and dependent degree, we can distinguish the current condition of driving safety with certain class level and put forward some improved measures. The dependent function and dependent degree of driving safety status under different driving intention (driving at constant speed, taking acceleration, taking deceleration, and lane change) are shown in Tables 5–8 respectively [37, 38].

In this study case, the headway between the evaluated vehicle and preceding vehicle is 1.98 s, the vehicle speed is

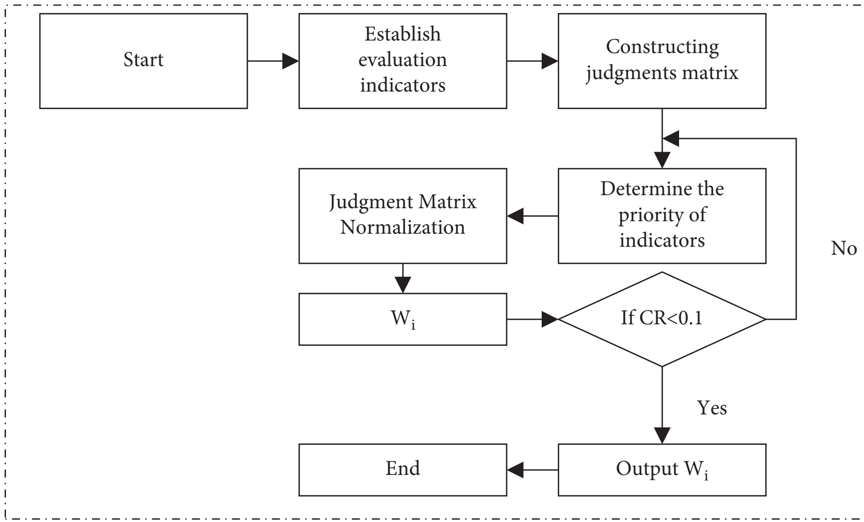

FIGURE 2: Weight determination based on AHP.

TABLE 2: Consistency index of random number.

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.9	1.12	1.24	1.38	1.41	1.46

53.3 km/h, the adhesion coefficient of pavement surface is 0.62, and the visibility in traffic environment is 175 m. The index weights calculated based on AHP obtain the parameters, i.e., TTC = 0.3825, Speed = 0.1006, Visibility = 0.0641, Adhesion coefficient = 0.1596, Driving intention = 0.2504, Driver fatigue = 0.0428 were obtained. Then, the evaluation results of driving safety under driving intention of "driving at constant speed" are shown in Table 5, the study case results show the driving safety status takes the maximum dependent degree 0.1661 with the "Less dangerous" (grade 2), as a result, the current driving safety status belongs to less dangerous. The evaluation results of driving safety under driving intention of "taking acceleration" are shown in Table 6, the study case results show the driving safety status takes the maximum dependent degree 0.1218 with the "Dangerous" (grade 1), as a result, the current driving safety status belongs to dangerous. The evaluation results of driving safety under driving intention of "taking deceleration" are shown in Table 7, the study case results show the driving safety status takes the maximum dependent degree 0.0048 with the "Safe" (grade 4), as a result, the current driving safety status belongs to safe. The evaluation results of driving safety under driving intention of "taking lane change" are shown in Table 8, the study case results show the driving safety status takes the maximum dependent degree 0.1873 with the "Less safe" (grade 3), as a result, the current driving safety status belongs to less safe. The results show that it will lead to maximum crash risk if driver take acceleration under the setting conditions, it is consistent with the practical situation in real traffic environment.

Furthermore, we selected ANN and SVM models as comparison models. Considering data accessibility and model characteristics, traditional Back Propagation Neural Network and linear SVM with hard margin are adopted. Hidden layer of ANN is set to be 3 and abnormal value penalty factor of SVM is set to be 0.5. The scoring process is conducted based on the receiver operating characteristics (ROC) curve, as shown in Figures 3(a) and 3(b), which can evaluate how competent the model is at predicting vehicle collision or noncollision risk scenarios through a true positive rate (TPR) versus false positive rate (FPR) graph. In this study, we classify the low vehicle crash risk into a negative set, whereas the high and moderate crash risk is classified into a positive set. The scoring results in Figure 3(b) show that the overall accuracy of the proposed model for vehicle crash risk prediction is approximately 95.1%, whereas the ANN and SVM models achieved overall accuracies of 91.9% and 88.7%, respectively.

These findings partially demonstrate that the proposed model framework can more accurately capture hiding patterns from a series of vehicle motion data. We take advantage of the ROC curve for this research because the overall accuracy and error rate of the model performance will be suspicious if the collected samples were strongly biased to the majority class. Under this situation, we use ROC curve indexes to evaluate the vehicle collision risk assessment models for different sample distributions. The TPR represents the percentage of risky driving cases that are correctly predicted as such, and the true negative rate (TNR = 1 – FPR) represents the portion of safety driving cases that are correctly forecasted as having such a condition. Thus, a balance between TPR and TNR in the ROC graphs will be consistent with the ground truth even if the positive and negative cases collected are highly skewed. The overall accuracy indicates the total ratio of correctly predicted driving safety status, and the area under each ROC curve (AUC) shown in Figure 3(b), that is, $ACU_{\text{Propoded model}} = 0.8967 ACU_{\text{ANN}} = 0.8883$ and $ACU_{\text{SVM}} = 0.745$ compares the general usefulness and overall performance of each model. Consequently, the proposed model is consistently superior to other benchmark models according to its area under the curve (AUC) in the

Table 3: Value of safety indices for driving motor vehicle

Attribute	Time to collision (s)	Speed (km/h)	Visibility (m)	Adhesion coefficient	Driving intention	Driver fatigue
Value	**1.98**	**53.3**	**175**	**0.62**	**1**	**2.5**

Table 4: Attribute weight of driving safety related factors.

Attribute	Time to collision	Speed	Visibility	Adhesion coefficient	Driving intention	Driver fatigue
Value	**0.3825**	**0.1006**	**0.0641**	**0.1596**	**0.2504**	**0.0428**

Table 5: Dependent degree of driving safety with driving at constant speed.

Attribute	Safety grade			
	Dangerous (grade 1)	Less dangerous (grade 2)	Less safe (grade 3)	Safe (grade 4)
Time to collision (s)	**0.0200**	**−0.0149**	**−0.3422**	**−0.5062**
Speed (km/h)	**−0.3646**	**−0.1271**	**0.3367**	**−0.2217**
Visibility (m)	**−0.4167**	**−0.3000**	**−0.1250**	**0.4990**
Pavement slippery (adhesion coefficient)	**−0.4571**	**−0.2400**	**0.4211**	**−0.1915**
Driving intention	**0**	**1.0000**	**0**	**0**
Driver fatigue	**0.1667**	**−0.1935**	**−0.5902**	**−0.7253**
Dependent degree	**−0.1216**	**0.1661**	**−0.0631**	**−0.2456**

Table 6: Dependent degree of driving safety with taking acceleration.

Attribute	Safety grade			
	Dangerous (grade 1)	Less dangerous (grade 2)	Less safe (grade 3)	Safe (grade 4)
Time to collision (s)	**0.0200**	**−0.0149**	**−0.3422**	**−0.5062**
Speed (km/h)	**−0.3646**	**−0.1271**	**0.3367**	**−0.2217**
Visibility (m)	**−0.4167**	**−0.3000**	**−0.1250**	**0.4990**
Pavement slippery (adhesion coefficient)	**−0.4571**	**−0.2400**	**0.4211**	**−0.1915**
Driving intention	**1.0000**	**0**	**0**	**0**
Driver fatigue	**0.1667**	**−0.1935**	**−0.5902**	**−0.7253**
Dependent degree	**0.1288**	**−0.0843**	**−0.0631**	**−0.2456**

Table 7: Dependent degree of driving safety with taking deceleration.

Attribute	Safety grade			
	Dangerous (grade 1)>	Less dangerous (grade 2)	Less safe (grade 3)	Safe (Grade 4)
Time to collision (s)	**0.0200**	**−0.0149**	**−0.3422**	**−0.5062**
Speed (km/h)	**−0.3646**	**−0.1271**	**0.3367**	**−0.2217**
Visibility (m)	**−0.4167**	**−0.3000**	**−0.1250**	**0.4990**
Pavement slippery (adhesion coefficient)	**−0.4571**	**−0.2400**	**0.4211**	**−0.1915**
Driving intention	**0**	**0**	**0**	**1.0000**
Driver fatigue	**0.1667**	**−0.1935**	**−0.5902**	**−0.7253**
Dependent degree	**−0.1216**	**−0.0843**	**−0.0631**	**0.0048**

Table 8: Dependent degree of driving safety with taking lane change.

Attribute	Safety grade			
	Dangerous (grade 1)	Less dangerous (grade 2)	Less safe (grade 3)	Safe (Grade 4)
Time to collision (s)	**0.0200**	**−0.0149**	**−0.3422**	**−0.5062**
speed (km/h)	**−0.3646**	**−0.1271**	**0.3367**	**−0.2217**
Visibility (m)	**−0.4167**	**−0.3000**	**−0.1250**	**0.4990**
Pavement slippery (adhesion coefficient)	**−0.4571**	**−0.2400**	**0.4211**	**−0.1915**
Driving intention	**0**	**0**	**1.0000**	**0**
Driver fatigue	**0.1667**	**−0.1935**	**−0.5902**	**−0.7253**
Dependent degree	**−0.1216**	**−0.0843**	**0.1873**	**−0.2456**

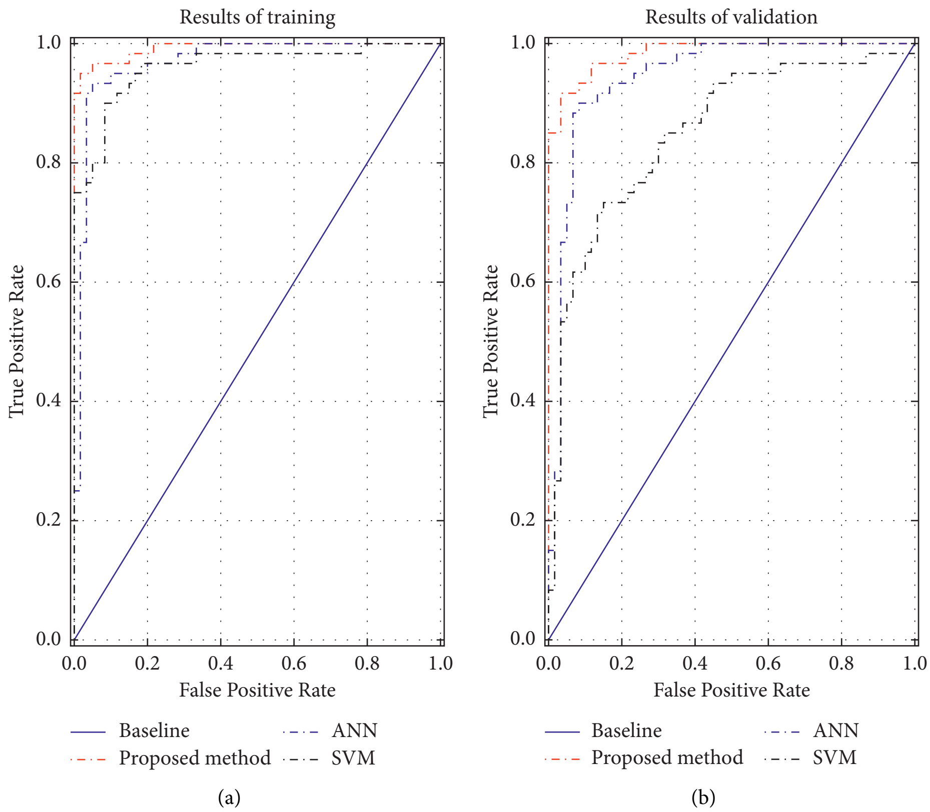

Figure 3: Overall performance of vehicle crash risk assessment models compared to observed dataset in model training procedure (a) and testing procedure (b), the vertical axis is the TPR, which indicates the correctly predicted crash cases, whereas the horizontal axis is the FPR, indicating the incorrectly predicted crashes.

ROC graph. The ANN model is relatively lower than the proposed model but still provides a satisfactory performance, whereas the SVM model ranked the lowest on these measures.

5. Conclusions and Recommendations

This paper attempts to promote the use of multiple information and multi-level analysis in crash prediction models, since factors from driver, vehicle, road, and environment can all affect the driving safety. However, traditional collision prediction models, such as the widely used safe distance model, cannot take into account many types of information. In order to take the multiple factors above into account, a model structure, which can provide multi-level analysis for coping with the heterogeneity among multiple pieces of data, is required. For this, a three-level, AHP-ME model is innovatively proposed in this paper to integrate multi-level factors into traffic crash analysis.

To appropriately model the potential cross-group heterogeneities in multi-level data, a methodological framework is proposed and then established. In this framework, hierarchical models that allow multi-level data structure to be explicitly specified and estimated are employed. Analytic Hierarchy Process (AHP) and Matter Element (ME) Model is introduced and recommended to calibrate the proposed hierarchical models. The practicality of the proposed method is illustrated through the severity analysis of simulated crash data. The illustrative example shows the flexibilities and effectiveness of the AHP-ME hierarchical method in modeling multi-level structure existing in multiple crash factors. Meanwhile, the ANN and SVM models are selected as the comparison models. The accuracy of the model proposed in this paper is always better than that of the ANN and SVM models, which can predict the vehicle collision risk more accurately.

The proposed AHP-ME analysis has a great potential in comprehensively assessing crash risk and therefore can be integrated into an ADAS. While most of previous studies cannot cope with the multi-level structure existing in multiple factors, this study suggests the importance of accounting for the cross-group heterogeneities in reliable estimation of various risk factors as well as accurate prediction of crash risk. In the future intelligent network environment, the model can be further expanded to consider the collision problems of more complex scenes in actual driving, such as continuous overtaking and long downhill and further improve the accuracy and real-time performance of the driver intention recognition model.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Ran Wei visualized and investigated the study, wrote the original draft, noted the data duration, developed the methodology, wrote, reviewed, and edited the manuscript, carried out funding acquisition, and administrated the project. Song Chen developed the methodology and wrote, reviewed, and edited the manuscript. Saifei Zhang conceptualized the study, wrote the original draft, developed the methodology, and wrote, reviewed, and edited the manuscript. Jiaqi Zhang developed the methodology, wrote, reviewed, and edited the manuscript, and conceptualized the study. Rujun Ding conceptualized the study, wrote the original draft, and wrote, reviewed, and edited the manuscript. Jiang Mi review and revised the literature.

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References

[1] T. Jin, H. Xia, and S. Gao, "Reliability analysis of the uncertain fractional-order dynamic system with state constraint," *Mathematical Methods in the Applied Sciences*, vol. 45, no. 5, pp. 2615–2637, 2022.

[2] Z. Xu, Z. Wang, J. Li, T. Jin, X. Meng, and S. Gao, "Dendritic neuron model trained by information feedback-enhanced differential evolution algorithm for classification," *Knowledge-Based Systems*, vol. 233, Article ID 107536, 2021.

[3] T. Jin, S. Gao, H. Xia, and H. Ding, "Reliability analysis for the fractional-order circuit system subject to the uncertain random fractional-order model with Caputo type," *Journal of Advanced Research*, vol. 32, no. 1, pp. 15–26, 2021.

[4] T. Jin, H. Xia, and H. Chen, "Optimal control problem of the uncertain second-order circuit based on first hitting criteria," *Mathematical Methods in the Applied Sciences*, vol. 44, no. 1, pp. 882–900, 2020.

[5] T. Xu, J. Gao, J. Liu, C. Zhao, and G. Liu, "A field study for evaluating the effectiveness of vehicle collision warning systems," *Transport Information and Safety*, vol. 40, no. 01, pp. 153–161, 2022.

[6] H. Tang, J. Zhang, and G. Liu, "A method for predicting frontal crash grade," *Automotive Engineering*, vol. 44, no. 03, pp. 392–398, 2022.

[7] C. Yang and H. Guan, "Research on safe distance between vehicles for freeway anti-collision system," *Process Automation Instrumentation*, vol. 29, pp. 19–21, 2008.

[8] T. Zhou and J. Zhang, "Analysis of commercial truck drivers' potentially dangerous driving behaviors based on 11-month digital tachograph data and multilevel modeling approach," *Accident Analysis & Prevention*, vol. 132, no. C, Article ID 105256, 2019.

[9] D. Hou, G. Liu, F. Gao, K. Li, and X. Lian, "State key laboratory of automotive safety and energy," *Automotive Engineering*, vol. 7, pp. 187–199, 2005.

[10] F. Gao, X. Yang, and J. Wang, "Virtual realization of active avoiding collision of vehicles' intelligent running," *Journal of Mechanical Engineering*, vol. 45, no. 08, p. 203, 2009.

[11] L. He, *Intelligent Transport System-Research on Millimeter Wave Radar for Automotive Anti-collision Technique and experiment*, Southeast University, Dhaka, 2003.

[12] A. Jamson, F. Lai, and O. Vehiclesten, "Potential benefits of an adaptive forward collision warning system," *Transportation Research Part C: Emerging Technologies*, vol. 16, pp. 471–484, 2007.

[13] Y. Tang, Z. Jiang, Y. Bai, and Y. Fang, "Model of vehicle safety distance for collision avoidance and simulation study," *Journal of Liaoning University of Technology (Natural Science Edition)*, vol. 28, pp. 324–326, 2008.

[14] T. Zhou, W. Wu, L. Peng et al., "Evaluation of urban bus service reliability on variable time horizons using a hybrid deep learning method," *Reliability Engineering & System Safety*, vol. 217, no. 9, pp. 5721–5736, 2021.

[15] Z. Tian, F. Liu, Y. Deng, H. Dai, and S. Lei, "Study on the mathematics model for the forewarning system of automobile rear-end collision avoidance," *Journal of Wuhan University of Technology (Information & Management Engineering)*, vol. 4, pp. 590–593, 2009.

[16] K. Vogel, "A comparison of headway and time to collision as safety indicators," *Accident Analysis & Prevention*, vol. 35, pp. 427–433, 2003.

[17] T. Ayres, L. Li, D. Schleuning, and D. Young, "Preferred time-headway of highway drivers," in *Proceedings of the ITSC 2001. 2001 IEEE Transactions on Intelligent Transportation Systems*, pp. 826–829, Oakland, CA, USA, August 2001.

[18] W. Guo, *Research on Methods of Traffic Conflict Discrimination*, Jilin university, Changchun, 2008.

[19] Y. He, S. Yang, C. Y. Chan, L. Chen, and C. Wu, "Visualization analysis of intelligent vehicles research field based on mapping knowledge domain," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 9, pp. 5721–5736, 2021.

[20] Y. He, C. Sun, H. Huang et al., "Safety of micro-mobility: riders' psychological factors and risky behaviors of cargo TTWs in China," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 80, pp. 189–202, 2021.

[21] R. Möbus, M. Baotic, and M. Morari, "Multi-object adaptive cruise control," in *HSCC'03 Proceedings of the 6th International Conference on Hybrid Systems: Computation and Control*, pp. 359–374, Springer, Berlin, Heidelberg, 2003.

[22] E. Sonja, "The intention to commit driving violations-a qualitative study," *Transportation Research Part F*, vol. 9, pp. 412–426, 2006.

[23] Y. Ren, H. Xu, X. Li, W. Wang, and J. Xu, "Research on module of drivers' steering reaction in simulative tail-crashing environment," *Journal of Transportation Systems Engineering And Information Technology*, vol. 7, no. 3, pp. 94–99, 2007.

[24] J. Shi, Y. Wu, B. Zhuo, Y. Ma, and X. Xu, "Identification and analysis of driver's active safety factors," *Journal of Shanghai Jiaotong University*, vol. 4, pp. 441–444, 2000.

[25] S. Li, J. Tian, X. Sha, W. Sun, and L. Wang, "Identification of vehicle risk status based on fuzzy comprehensive evaluation and bp neural network," *Journal of Jilin University(Engineering and Technology Edition)*, vol. 41, pp. 1610–1613, 2011.

[26] X. Song, G. Xiao, and G. Jia, “Study on the locomotive operation safety assessment based on analytical hierarchy process,” *Journal of Safety Science and Technology*, vol. 6, pp. 86–89, 2006.
[27] J. Liu, B. Xu, Y. Liang, and R. Ma, “Traffic safety assessment of expressway in the accident,” *Journal of Chang’an University (Natural Science Edition)*, vol. 32, pp. pp79–82, 2012.
[28] Z. Liu, P. Wang, H. Qin, J. Zhong, and S. Song, “Study on intelligent vehicle anti-collision fore warning technology based on multi-information detection,” *China Safety Science Journal*, vol. 20, pp. 154–158, 2010.
[29] C. Liao, X. Huang, and Y. Chai, “A study on the system of decision-making for vehicle collision avoidance based on information fusion,” *Journal of System Simulation*, vol. 16, pp. 1589–1596, 2004.
[30] Y. Zhou, *A Study on the System of Vehicle Collision Avoidance Based on Multi-Sensor Information Fusion Algorithm*, Northeastern University, Boston, 2008.
[31] J. Tian, S. Li, W. Sun, Z. Yang, and L. Wang, “Evaluation model of dynamic vehicle safety status with vehicle-way synergy,” *Journal of Harbin Institute of Technology*, vol. 44, pp. 132–135, 2012.
[32] B. Chang, H. Tsai, and C. Young, “Intelligent data fusion system for predicting vehicle collision warning using vision/GPS sensing,” *Expert Systems with Applications*, vol. 37, no. 3, pp. 2439–2450, 2010.
[33] R. Toledo-Moreo and M. Zamora-Izquierdo, “Collision avoidance support in roads with lateral and longitudinal maneuver prediction by fusing GPS/IMU and digital maps,” *Transportation Research Part C: Emerging Technologies*, vol. 18, no. 4, pp. 611–625, 2010.
[34] M. Lu, “Modelling the effects of road traffic safety measures,” *Accident Analysis & Prevention*, vol. 38, no. 3, pp. 507–517, 2006.
[35] N. Kaempchen, B. Schiele, and K. Dietmayer, “Situation assessment of an autonomous emergency brake for arbitrary vehicle-to-vehicle collision scenarios,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 10, no. 4, pp. 678–687, 2009.
[36] F. G. M. Al-Azab and M. A. Ayu, “Web based multi criteria decision making using ahp method,” in *Proceedings of the 3rd International Conference on Information and Communication Technology for the Moslem World (ICT4M) 2010*, pp. A6–A12, Jakarta, Indonesia, December 2010.
[37] W. Yang, J. Liu, and J. Liu, “Active anti-collision warning model considering the driver’s intention of the vehicle ahead under internet of vehicles,” *Journal of Mechanical Engineering*, vol. 57, no. 22, pp. 284–295, 2021.
[38] Y. Wang, *Study on Vehicle Forward Collision Avoidance Early Warning System Based on Driver and Environment Characteristics*, Chang’an University, Xi’an, 2021.