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Review

Review of Intelligent Vehicle Driving Risk Assessment in Multi-Vehicle Interaction Scenarios

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Abstract: With the rapid breakthroughs in artificial intelligence technology and intelligent manufacturing technology, automotive intelligence has become a research hotspot, and much progress has been made. However, a skeptical attitude is still held towards intelligent vehicles, especially when driving in a complex multi-vehicle interaction environment. The interaction among multi-vehicles generally involves more uncertainties in vehicle motion and entails higher driving risk, and thus deserves more research concerns and efforts. Targeting the safety assessment issue of complex multi-vehicle interaction scenarios, this article summarizes the existing literature on the relevant data collection methodologies, vehicle interaction mechanisms, and driving risk evaluation methods for intelligent vehicles. The limitations of the existing assessment methods and the prospects for their future development are analyzed. The results of this article can provide a reference for intelligent vehicles in terms of timely and accurate driving risk assessment in real-world multi-vehicle scenarios and help improve the safe driving technologies of intelligent vehicles.

Keywords: autonomous vehicle; risk assessment; driving risks; multi-vehicle interaction

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1. Introduction

With the rapid advancements in artificial intelligence technology and intelligent manufacturing technology, automotive intelligence has captured the attention of the public and emerged as a prominent area of research in the global automotive industry. Intelligent vehicles are equipped with advanced sensors (such as LiDAR, cameras, millimeter wave radar, etc.), controllers, actuators, and other devices to achieve intelligent driving through computer vision, multi-source data fusion, automatic control, and other technologies. Although intelligent vehicles have made tremendous progress thanks to rapidly developing technologies, the general public still holds a skeptical attitude, especially when driving in a complex multi-vehicle interaction environment. The driving risk assessment for such a complex environment can be challenging because the interaction among multi-vehicles generally involves more uncertainties and entails higher driving risk. Therefore, effective risk assessment methods are particularly important for intelligent vehicle driving in complex multi-vehicle interaction scenarios.

Many critical metrics have been proposed to evaluate the situation criticality for intelligent vehicles in the literature over the years. The most commonly used risk metrics are based on Time-to-X indicators, such as Time to Collision and Time to Steer. Although these indicators are simple and easy to calculate, they are usually only applicable to specific longitudinal or lateral scenes, making it difficult to fully capture the vehicle interaction process in multi-vehicle scenarios that integrate both longitudinal and lateral driving features. In order to ensure the driving safety of autonomous vehicles in the actual complex road environment, timely and accurate assessment of the safety situation in multi-vehicle interaction scenarios has become a problem that demands much research attention. However, while existing survey literature has extensively explored achievements in risk assessment for two-vehicle interactions, there is comparatively less focus on intelligent vehicles in multi-vehicle interaction scenarios [1–5]. Therefore, the academic community still lacks in-depth analysis and systematic summary of the solutions to the problem.

To overcome the aforementioned challenges, focusing on the driving risk assessment problem of intelligent vehicles in multi-vehicle interaction scenarios, this article summarizes the existing literature on interaction data collection, vehicle interaction mechanisms, and multi-vehicle interaction risk evaluation methods. The shortcomings of existing literature methods and prospects for future technologies are also analyzed and discussed. The results of this article can provide a reference for intelligent vehicles in terms of timely and accurate driving risk assessment in real-world multi-vehicle scenarios and help improve the safe driving technologies of intelligent vehicles. The contributions of this study are two-fold as follows:

(1) This study summarizes the advantages and disadvantages of existing methods for evaluating the safety situation of intelligent vehicles in multi-vehicle interaction scenarios, which facilitates a better understanding and application of these methods for relevant researchers;

(2) This study points out the challenges and future research directions of intelligent vehicle safety situation assessment in multi-vehicle interaction scenarios, which provides potential research directions for relevant researchers and helps to promote the development of this field.

It should be noted that the multi-vehicle interaction scenario addressed in this article specifically pertains to a highway environment involving a minimum of three driving vehicles that dynamically interact with each other. Scenarios such as vehicle platooning and road intersections were excluded from consideration, as these scenarios entail distinct risk evolution mechanisms and are not the primary focus of this study. Relevant references in this article were collected using academic search engines (such as Google Academic) and databases (such as IEEE Xplore and ScienceDirect).

The remaining content of this article is arranged according to the following structure. The data collection methods for multi-vehicle interaction scenarios are introduced in Section 2. The mechanism of multi-vehicle interaction is described in Section 3. The risk assessment methods for two-vehicle interactions and multi-vehicle interactions are summarized and discussed, respectively, in Section 4. Challenges and future research directions are presented in Section 5. Section 6 concludes this paper. Figure 1 depicts the flowchart outlining the structure of this paper.

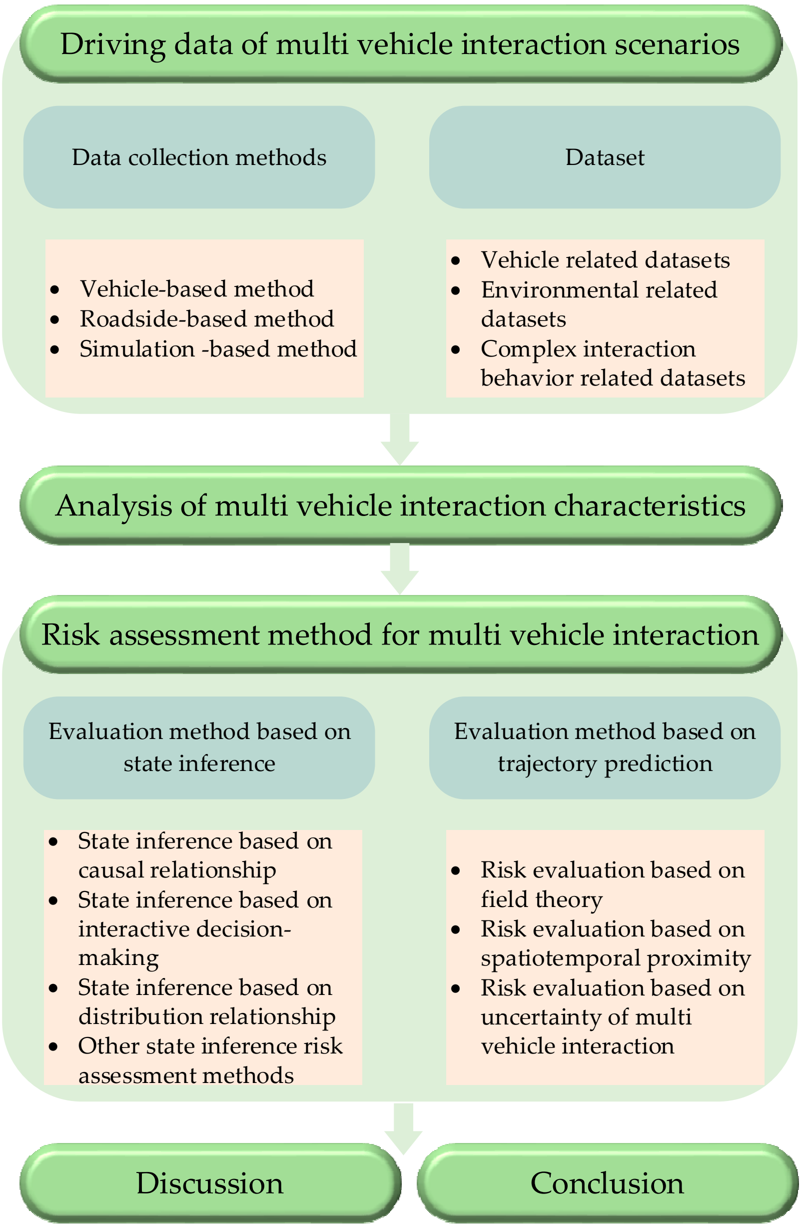

Figure 1. Research framework.

2. Data Collection for Multi-Vehicle Interaction Scenarios

In order to realize risk assessment in multi-vehicle interaction scenarios, it is necessary to first collect offline interaction data samples among multiple vehicles, based on which risk evaluation models are developed and trained; online multi-vehicle interaction information data are then fed into the obtained model to produce real-time risk assessment results. Therefore, obtaining multi-dimensional data characterizing multi-vehicle interaction scenarios is the foundation for conducting subsequent risk assessments.

At present, the data collection methods for multi-vehicle interaction can be roughly divided into three categories, including vehicle-based, roadside-based, and simulation-based methods, as shown in Table 1 [4].

Table 1. Data collection methods for multi-vehicle interaction scenarios.

Name	Method Description	Main Features
Vehicle-based method	Onboard sensors are utilized to obtain vehicle motion and driver characteristics data in a multi-vehicle environment (in the real world or driver-in-the-loop simulation); traffic conflicts are labeled manually [6].	Data collection and extraction are generally costly; the type and quantity of the test subjects are limited.
Roadside-based method	Roadside detectors/cameras or drones are employed to obtain vehicle trajectory data [7–9]; traffic conflicts can be labeled manually or by machine learning algorithms.	The data collection interval is flexible; object detection algorithms need careful calibration and validation.
Simulation-based method	Micro-level simulation software is used to build a multi-vehicle interaction environment [10,11]; conflict data are directly obtained from the software output.	Various types of multi-vehicle scenarios can be simulated; accuracy depends on the basic behavioral model and relevant assumptions within the simulation software.

In recent years, thanks to the continuous development of onboard software/hardware and intelligent algorithms, more autonomous driving datasets have been available for driving safety research. Such datasets can be utilized without being limited by experimental environments and technical conditions, making it convenient to conduct multi-vehicle interaction risk assessment analysis. Wang et al. [12] summarized three types of datasets, including vehicle-related datasets, driving environment datasets, and datasets containing complex behavioral interactions, part of which are shown in Table 2. Vehicle-related datasets mainly record data on vehicle operation status, driver operation, and vehicle internal status; environmental-related datasets provide information on a bird's eye view of the physical states of the traffic participants, high-definition map of the driving environment, and even classification of individual behaviors; complex interaction behavior related datasets aim at complicated traffic conditions and support the decision-making development [13].

Table 2. Dataset types and attributes [12].

Dataset Type	Dataset Name	Vehicle Operation Status Data	Driver Operation Data	Vehicle Internal Status Data
Vehicle-related datasets	EU Long term [14]	√	×	×
	Udacity [15]	√	√	×
	DDD17 [16]	√	√	√
		Bird's-eye view of physical state	**High-definition map**	**Behavior classification**
Environmental related datasets	Apollo Scape [17]	×	×	×
	NuScenes [18]	×	√	×
	WAYMO [13]	√	√	√
	NGSIM [19]	√	×	×
		Behavioral Interaction Description		
Complex interaction behavior-related datasets	Apollo Scape [17]	Interaction complexity is divided into three levels based on the number of moving objects in the scene.		
	WAYMO [13]	77.5% of the scenes contain multi-object interactions.		
	DoTA [20]	Dangerous scenes (near accidents) are included.		

3. Analysis of Multi-Vehicle Interaction Characteristics

During the driving process, intelligent vehicles need to monitor the behavior of surrounding vehicles in real time and make decisions on whether to maintain following or lane-changing behaviors. The characteristics of such interaction behavior between vehicles are of great significance to understanding the risk mechanism in complex multi-vehicle environments and serve as the foundation for constructing subsequent multi-vehicle interaction risk assessment methods.

The characteristics of multi-vehicle interaction behavior are often closely related to that of the two-vehicle pairs but have more uncertainty and complexity. Zhang et al. [21] observed a large amount of vehicle interaction behavior samples and described the typical interaction behavior process of the vehicle pairs as presented in Table 3. It can be seen that the typical interaction behavior patterns of vehicles can be roughly divided into four categories, including longitudinal, front cut-in, rear cut-in, and lateral behaviors. These behavior patterns exhibit variability in the initial state of the vehicle pair as well as their lateral and longitudinal speeds throughout the interaction process.

Table 3. Typical vehicle interaction behavior modes.

Category	Interactive Behavior	Initial State of Two Vehicles	Typical Characteristics of the Interaction Process		Conflicts during Interaction	Typical Scenarios
			Lateral Speed	Longitudinal Speed		
Longitudinal behavior	Normal following	Front and rear vehicles in the same lane with similar initial longitudinal speeds	Maintained approximately at zero	Maintained approximately the same	×	Smooth car following process
	Compressed following	The same with the normal following mode	Maintained approximately at zero	Front vehicle decelerates or rear vehicle accelerates	√	Unexpected incidents in the front
Front cut-in	Direct cut-in	Fast front and slow rear vehicles located on adjacent lanes	Front vehicle increases lateral speed and cuts into the front of the rear vehicle	Maintained approximately the same	×	Normal lane-changing process
	Coordinated cut-in	Slow front and fast rear vehicles located on adjacent lanes	Front vehicle increases lateral speed and cuts into the front of the rear vehicle	Front vehicle accelerates while rear vehicle decelerates	√	Vehicles leaving the main road for exit ramp
Rear Cut-in	Direct cut-in	Fast front and slow rear vehicles located on adjacent lanes	Rear vehicle increases lateral speed and cuts into the rear of the front vehicle	Maintained approximately the same	×	Vehicles changing lanes due to slow traffic in the front
	Coordinated cut-in	Slow front and fast rear vehicles located on adjacent lanes	Front vehicle increases lateral speed and waits to cut into the rear of the rear vehicle	Maintained approximately the same; coordinated in the relative position	√	Vehicles leaving the entrance ramp for the main road
Lateral behavior		Slow front and fast rear vehicles located on adjacent lanes	Rear vehicle has a high lateral speed and quickly approaches the adjacent lane	Maintained approximately the same	√	Vehicles changing to faster inner lanes

The above research only analyzes the interaction behavior within vehicle pairs. However, vehicles are not only influenced by the behavior of one adjacent vehicle but by the vehicle group composed of all surrounding vehicles, which can generate more complex interaction behaviors and needs further in-depth analysis.

4. Risk Assessment Method for Multi-Vehicle Interaction

This section provides a systematic review of the risk assessment methods for multi-vehicle interaction. Firstly, the traditional assessment methods for two-vehicle interaction and their limitations are outlined; then, the existing multi-vehicle interaction risk assessment methods in the literature are summarized and elaborated.

4.1. Risk Assessment of Interaction between Two Vehicles

The risk of two-vehicle interaction can be quantified in terms of vehicle proximity and collision avoidance intensity [22], based on which many scholars have established a series of Surrogate Safety Measures (SSM) to evaluate the risk of two-vehicle interactions [23]. SSM can be mainly divided into four subcategories, namely time-based SSM, distance-based SSM, deceleration-based SSM, and energy-based SSM, as shown in Figure 2.

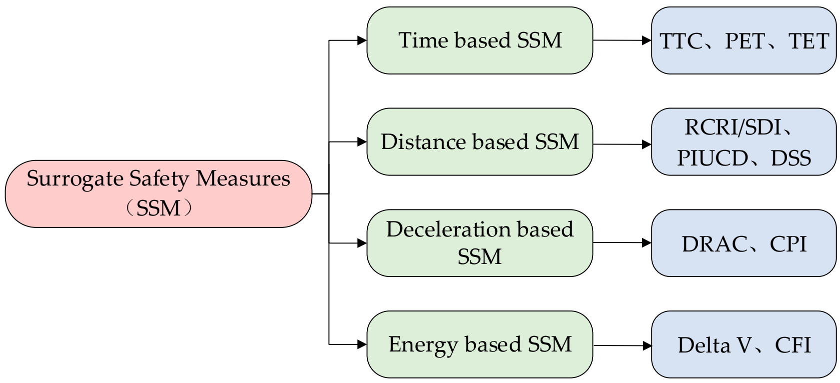

Figure 2. Overview of surrogate safety measures.

4.1.1. Time-Based SSM

Time-based SSM mainly includes Time to Collision (TTC), TTC-derived indicators, Post Encroachment Time (PET), and PET-derived indicators [24–41], as summarized in Table 4. TTC represents the proximity of road users to potential collision points, while PET reflects the proximity of road users to the actual collision points. Both of them emphasize the existence of conflicting paths but lack a description of the collision process. Statistics show that approximately one-third of current studies employed the indicator TTC or the indicator combinations with TTC and other SSMs.

Table 4. Time-based SSM.

Classification	Indicator	Definition	Limitations	Advantages
TTC and its derivative indicators	Collision to Time (TTC) [25–27]	The time for the two cars to collide at their current speed and direction	Evasive actions are not considered; threshold is required and can be sensitive to evaluation.	Commonly used; easy to measure
	Time Exposed Time-to-Collision (TET) [30,31]	The total time period when TTC is below the threshold	Threshold sensitivity; different TTC values (severity level) cannot be reflected.	The overall risk of a time period can be obtained.
	Time Integrated Time-to-Collision (TIT) [32,33]	The integration of TTC during the period when TTC is below the threshold	Threshold sensitivity; difficult to explain	Risk estimate varies according to different TTC values.
	Modified Time-to-collision (MTTC) [34–36]	A revised version of TTC that considers all possible longitudinal conflicts due to acceleration /deceleration	Threshold sensitivity; instantaneous acceleration data are difficult to obtain	More advanced than TTC; scenario differences are considered.

Table 4. *Cont.*

Classification	Indicator	Definition	Limitations	Advantages
PET and its derived indicators	Post- Encroachment Time (PET) [37–39]	The time interval between one party leaving and the other arriving at the conflict area	Threshold sensitivity; unable to reflect changes in interactive dynamics	Suitable for lane changing; easy to measure
	Headway (H) [40]	The time interval between two consecutive vehicles passing a given point on the road	The lateral movements caused by overtaking and lane changing are not considered.	Easy to measure
	Time Advance (TAdv) [41]	Another version of PET assumes road users do not change path and speed	Threshold sensitivity; strong assumption on constant speed and direction	Suitable for both longitudinal and lateral scenarios

4.1.2. Distance-Based SSM

Distance-based SSM characterizes risk by measuring the distance from the vehicle to the collision point, mainly including the Stop Distance Index (SDI), Potential Index for Collision with Urgent Deceleration (PICUD), Difference of Space distance and Stopping distance (DSS), etc. [42–46], as shown in Table 5.

Table 5. Distance-based SSM.

Indicator	Definition	Limitations	Advantages
Stop Distance Index (SDI) [44]	The minimum distance required to avoid collision with the front vehicle when it decelerates at the maximum deceleration rate until stops	Only applicable to the car following scenes	Easy to calculate
Potential Index for Collision with Urgent Deceleration (PICUD [45])	The distance between the two vehicles after they complete emergency braking	Threshold sensitive; lateral interactions are not considered	Suitable for collision severity evaluation
Difference of Space distance and Stopping distance (DSS) [46]	Another version of PICUD that takes the friction coefficient into account	Rarely used due to the fact that most friction information is not available in vehicle trajectory datasets	Suitable for collision severity evaluation under extreme roadway conditions

4.1.3. Deceleration-Based SSM

Deceleration-based SSM is generally determined by the ultimate braking capability of the vehicle and the required deceleration to avoid collisions [47–52]. It is commonly used to evaluate the intensity of evasive actions taken by drivers to avoid collisions during traffic conflicts. The commonly used deceleration-based SSM are shown in Table 6.

Table 6. Deceleration-based SSM.

Indicator	Definition	Limitations	Advantages
Deceleration Rate to Avoid the Crash (DRAC) [48–51]	The speed difference between the two vehicles divided by TTC	Only applicable to the car following scenes; threshold sensitivity	Easy to measure
Crash Potential Index (CPI) [52]	An extended version of DRAC by considering vehicle's maximum deceleration rate	Only applicable to longitudinal following situations; different DRAC values (severity level) cannot be reflected.	The overall risk of a time period can be obtained.

4.1.4. Energy-Based SSM

Energy-based SSM is established based on vehicle collision theory assuming collisions are inevitable [9,53–56]. Based on the conservation of momentum and kinetic energy, the energy released during the collision process can be calculated for various types of collisions and used to evaluate the severity of potential collisions. Typical energy-based SSMs are shown in Table 7.

Table 7. Energy-based SSM.

Indicator	Definition	Limitations	Advantages
Delta V [55]	Velocity changes in vehicle trajectory before and after the collision	Evasive actions are not considered; inelastic collision assumption	Easy to measure; consequence of collision is evaluated.
Conflict index (CFI) [56]	Kinetic energy released during collisions is estimated by combining PET with speed, mass, and relative angle.	Parameter calibration is required; difficult to explain	Both vehicle proximity and collision consequences are considered.

Based on the above summaries, it can be seen that the SSM-based risk evaluation methods mainly take kinematics measures into account (e.g., relative speed and distance, deceleration, mass, etc.). The advantages include simplicity in structure and high computational efficiency, making it suitable for quick assessment of real-time safety situations; the disadvantage is that the uncertainties in vehicle motion and interaction scenarios are often ignored, which limits the application scenarios of such evaluation methods, especially for complex multi-vehicle scenarios that feature more uncertain factors in vehicle interaction [57,58].

4.2. Risk Assessment of Multi-Vehicle Interaction

Depending on whether an accurate prediction of future vehicle trajectories is needed, this article divides the existing methods of multi-vehicle interaction risk assessment into two categories, including state inference-based assessment methods and trajectory prediction-based assessment methods, as shown in Figure 3. In particular, the evaluation method based on state inference generally employs Bayesian models, game theory models, or complex network models to directly depict (predict) the current (future) risk state among vehicles without making specific predictions on their future trajectories; trajectory prediction-based evaluation method, on the contrary, usually relies on the trajectory prediction results of the target vehicles for a period of time in the future, based on which the possibility and severity of collisions are calculated and determined.

4.2.1. Evaluation Method Based on State Inference

As mentioned in Section 2, high-resolution vehicle trajectory data can be widely applied to risk assessment of multi-vehicle interaction [59,60]. State inference-based evaluation methods usually directly depict and deduce current and future risk states using the historical trajectories of vehicles instead of their predicted future trajectories. In particular, these methods can be further categorized based on specific inference theories/methodologies, including the theory of causation, the theory of interactive decision making, distribution relationship characterization, and other state inference methodologies. Table 8 summarizes the evaluation method based on state inference.

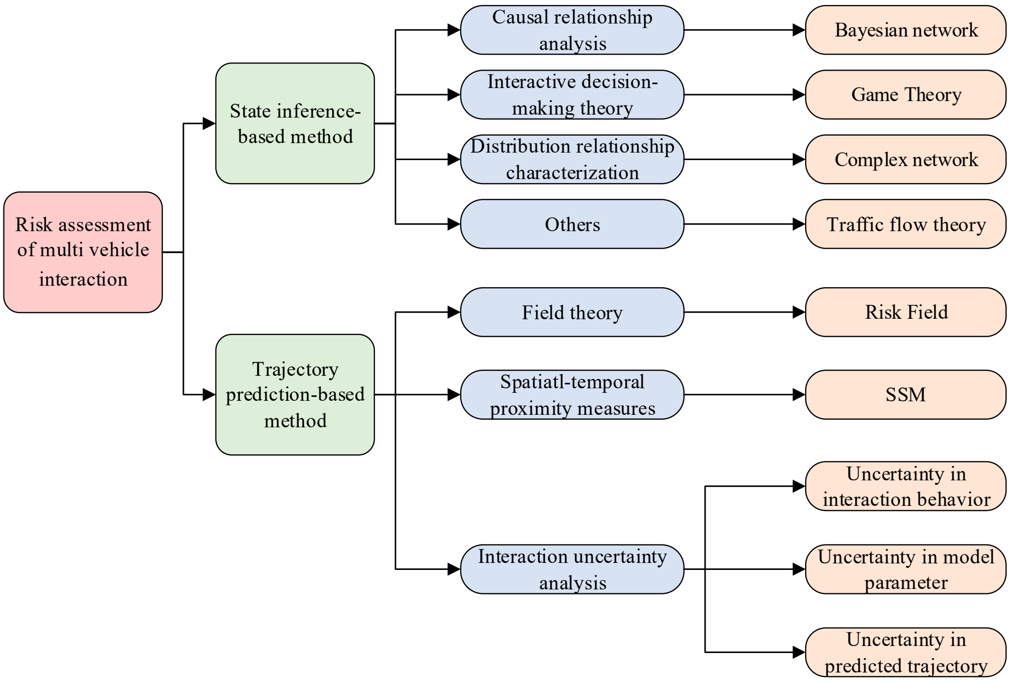

Figure 3. Classification of risk assessment methods for multi-vehicle interaction.

Table 8. Evaluation method based on state inference.

Classification	Description	Advantages	Limitations
Based on causal relationship [61–64]	Evaluating driving risk by quantitatively analyzing the relationship between risk-related variables (such as drivers, vehicle characteristics, and weather) and risk levels.	Normalized results across different scenarios (i.e., with good scenario applicability) can be obtained.	Difficult to solve and poor in real-time computing performance due to the large number of model parameters.
Based on interactive decision-making [65–70]	Viewing multi-vehicle interaction as a game process (with vehicles as participants in the game) and using game theory theories to analyze the risk relationships between vehicles.	Behavioral strategy can be defined for each vehicle (game player) to better mimic real-world scenarios.	Difficult to jointly model the overall gaming behavior of the multi-vehicle group.
Based on the distribution relationship [71,72]	Using network-based theory to describe the dynamic spatial distribution relationship among vehicles during multi-vehicle interaction for risk assessment.	The risk relationship among multi-vehicles can be fully captured.	Lacking empirical experience and experimental data.
Other state inference risk assessment methods [73,74]	Studying the evolution pattern of multi-vehicle driving risk of road sections from the perspective of macro traffic flow.	Influencing factors on risk outcome can be identified for accident prevention strategy development.	Ignoring the occurrence and development process of vehicle interaction risks and cannot directly quantify the risk of micro-level interaction behaviors.

(1) State inference based on causal relationship.

The method based on causality mainly evaluates driving risk by quantitatively analyzing the relationship between risk-related variables (such as drivers, vehicle characteristics, and weather) and risk levels [61–64]. Zhu et al. [61] proposed a Bayesian hierarchical model for real-time prediction of the probability of vehicle risk at highway entrances and exits under different risk levels. Three layers were established, including the vehicle physical state layer, multi-vehicle interaction layer, and risk probability layer. In particular, the physical state layer dynamically inputs kinematic parameters such as vehicle position, speed, acceleration, and steering angle; the multi-vehicle interaction layer includes motion variation parameters such as the changes in distance, speed, acceleration, and steering angle between the interacting vehicles; the risk probability layer outputs the collision probability index (CPI) that quantifies the interaction risk. Katrakazas et al. [62] proposed a risk assessment method based on an interactive motion perception model and dynamic Bayesian networks (DBNs). In order to predict the real-time collision risk of all vehicles on a road segment (300–500 m in length) in real time, two interrelated risk domains, including the network level risk domain and the vehicle level risk domain, were introduced. In particular, the network-level risk domain was established based on DBN using road traffic condition data (such as average speed, average flow rate, average occupancy rate, etc.). Wang [64] proposed a risk distance coefficient K_d that integrates the attention, speed, and interaction perception capabilities of traffic participants, based on which a DBN risk assessment model was constructed and applied to vehicle motion planning to improve the safety of vehicle operation.

The risk assessment method based on causality can output normalized results across different scenarios (i.e., with good scenario applicability). However, this method usually features a large number of model parameters, resulting in high difficulty in solving and poor real-time computing performance.

(2) State inference based on interactive decision making

Game theory is a theory that studies the interaction between decision makers' strategic behaviors, which fits into the realm of interaction behaviors between road users, and has been widely used in the field of multi-vehicle interaction risk assessment [65–67]. Cheng [68] established a joint model of mandatory lane change gaming and trajectory planning. Based on the game characteristics between the subject vehicle and its front and rear vehicles on both the target lane and the initial lane, a risk assessment module was developed using the minimum safety distance index to predict the magnitude of the mandatory lane change risk. Sheikh et al. [69] analyzed the game behavior between the subject vehicle and its surrounding vehicles (the front vehicles on both the initial lane and the target lane), based on which the possibility of collisions caused by abnormal speeding during lane changing was predicted, and the possible location of collisions was determined by the shock wave theory. Yu et al. [70] proposed a lane-changing model based on game theory, which judged the lane-changing intention of surrounding vehicles using turn signals and lateral displacement, and selected the optimal strategy considering the future response of surrounding vehicles, where a combination function of safety benefits and spatial benefits were designed to comprehensively evaluate the safety of the lane changing behavior.

In the risk assessment method based on interactive decision making, game characteristics are usually analyzed for each subject–other vehicle pair (i.e., the subject vehicle and one of its adjacent vehicles) rather than the multi-vehicle group, which may ignore the gaming behaviors among the surrounding vehicles that can also affect the overall risk state of the subject vehicle.

(3) State inference based on distribution relationship

Based on the dynamic spatial distribution relationship among the vehicles during the driving process, some scholars have applied complex network theory to risk assessment of multi-vehicle interaction. Cai et al. [71] proposed a multi-vehicle interaction complex network generation algorithm where each moving vehicle was treated as a node. A variable Gaussian safety field model was established for each node to reflect their dynamic field characteristics. The overlap area between different safety fields was measured as the interaction risk level between vehicles and was modeled as the weights for the node links. Taking the road boundary as the node constraint, the complex network-based risk assessment model was finally obtained. Some other studies based on complex network theory have explored the relationship between traffic accidents and risk factors and provided suggestions for selecting risk variables for multi-vehicle interaction assessment. Chen et al. [72] established a complex network for traffic accidents using a variety of factors, including driver, vehicle, and weather characteristics. Key risk factors and risk propagation relationships were analyzed and identified based on typical network indicators such as node degree and median centrality.

The risk assessment method based on distribution relationships intrinsically simulates the dynamic interaction behavior among multiple vehicles using complex network theory, which fits well into the scope of multi-vehicle interaction risk assessment. However, so far, only a few researchers have employed this kind of method and generally lack empirical experience and experimental data [71].

(4) Other state inference risk assessment methods

Some scholars have studied the evolution pattern of multi-vehicle driving risk on road sections from the perspective of macro traffic flow. Mohammadian et al. [73] studied the interaction behavior of all following vehicles in a six-lane traffic flow of highway and proposed a hybrid framework that combines traditional probability models and machine learning models to evaluate the safety state of the traffic flow. Liu et al. [74] divided highway traffic flow into three stages, including free flow, synchronous flow, and wide-moving jam, based on traffic flow variables. The collision risk of different traffic stages was evaluated, respectively, using Time Exposed Time-to-Collision (TET) and Time Integrated Time-to-Collision (TIT). These studies mostly focused on the results of risky vehicle interactions and examined the correlation between risk outcomes and influencing factors. However, they usually ignore the occurrence and development process of vehicle interaction risks and cannot directly quantify the risk of micro-level interaction behaviors.

4.2.2. Evaluation method based on trajectory prediction

Trajectory prediction refers to outputting the predicted trajectories of the target vehicles over a period of time (usually 1 s for short-term and 3–5 s for medium-term) based on given information (such as vehicle dynamics, historical trajectories, traffic rules, etc.), which can be of great significance for functional modules such as path planning and driving risk assessment. The trajectory prediction-based risk evaluation method analyzes the future spatiotemporal distribution of different vehicle trajectories based on the trajectory prediction results, based on which risk assessment for multi-vehicle interaction is ultimately achieved. Table 9 summarizes the evaluation method based on trajectory prediction.

Table 9. Evaluation method based on trajectory prediction.

Classification	Description	Advantages	Limitations
Based on field theory [75–78]	Calculating the interaction forces and field strength distribution between vehicles given the predicted trajectories, based on which the risk level of each vehicle is determined.	Driving risk can be comprehensively characterized and is applicable to complex multi-vehicle interaction scenarios.	Having a large number of coefficients that are difficult to calibrate may affect the accuracy of the evaluation results.

Table 9. *Cont.*

Classification	Description	Advantages	Limitations
Based on spatiotemporal proximity [58,79–89]	Quantifying the multiple vehicle interaction risks by measuring the spatiotemporal proximity between the predicted trajectories of the subject vehicle and its surrounding vehicles.	The method can quickly assess the risk state and has high computational efficiency.	The uncertainties of surrounding vehicles are hardly fully considered due to the relatively strong assumptions made for spatiotemporal proximity index.
Based on uncertainty of multi-vehicle interaction [90–97]	Quantifying the multiple vehicle interaction risks by considering the uncertainty of the driving intentions of surrounding vehicles.	The interaction behavior between multiple vehicles can be analyzed to mimic the actual traffic scene.	The computational complexity is often high and relies on accurate modeling of the vehicle interaction behavior.
	Quantifying the multiple vehicle interaction risks by considering the uncertainty in the relevant control parameters of the vehicle motion model.	The consideration of the uncertainty of model parameters can improve the accuracy of evaluation results.	Requiring accurate parameter estimation methods may lead to significant deviations in evaluation results if estimated parameters are not accurate.
	Quantifying the multiple vehicle interaction risks by considering the overall uncertainty of trajectory prediction in the time domain.	More reliable results can be achieved considering the uncertainty in mean distribution of the predicted trajectories.	Unconventional situations such as emergencies cannot be accounted for, and the evaluation results for abnormal situations may be inaccurate.

(1) Risk evaluation based on field theory

The trajectory prediction results of the surrounding vehicles are usually combined with field theory for the risk assessment of multi-vehicle interaction. Scholars studying risk assessment methods based on field theory believe that the interaction risk value is directly related to the motion state and spatial distribution of the interacting vehicles and can be quantified by analyzing the range and distribution of field strength generated by the vehicles. Since Khatib [75] first proposed the method of artificial potential field (APF), field theory has been widely used in the field of driving safety, and many research studies have emerged using field strength to describe vehicle interaction risk. Wang et al. [76] proposed a driving risk field model to describe the interaction among road users, which constitutes of kinetic energy field, potential energy field, and behavioral field, providing new ideas for risk analysis of multi-vehicle interaction in the two-dimensional space of highways. Freddy et al. [77] proposed a probabilistic driving risk field (PDRF), which predicts the possible positions of the interacting vehicles in discrete future time steps by assuming a normal distribution of the vehicle acceleration. The probability of vehicle collision was then represented by the possibility of vehicle position overlapping, and the product of collision probability and expected collision energy was finally calculated as the risk field strength. Based on driving behavior identification, Wang [78] built a vehicle trajectory prediction model using encoding-decoding Long Short-Term Memory (LSTM) and employed Mixed Density Networks (MDN) to transform the predicted trajectories into the possible future trajectory domains, based on which the concept of trajectory field was further proposed using field theory. The collision risk was finally assessed by calculating the total field strength of the evaluated vehicle generated by its surrounding vehicles.

The evaluation method based on field strength theory can characterize driving risk more comprehensively thanks to its wide variety of factors taken into consideration and is applicable to complex multi-vehicle interaction scenarios (i.e., not limited to specific scenarios such as car following or lane changing). However, this evaluation method has a large number of coefficients that are difficult to calibrate, which may affect the accuracy of the evaluation results.

(2) Risk evaluation based on spatiotemporal proximity

On the basis of the predicted vehicle trajectories, multiple vehicle interaction risks can be quantitatively evaluated by measuring the spatiotemporal proximity between the subject vehicle and its surrounding vehicles, using indicators such as time to collision (TTC), stopping distance index (SDI), Deceleration Rate to Avoid the Crash (DRAC), and rear end collision index (RCRI) [79–85]. Ma et al. [86] used the Kalman Filter (KF) algorithm to predict vehicle trajectories and speeds, based on which the traffic conflict area between the left-turning vehicles and straight-going vehicles in the opposite direction was determined. By recording the time each vehicle passed through the conflict area, the Post Encroachment Time (PET) was calculated and combined with vehicle motion information to identify the collision probability. Zhang [87] proposed a driving intention-based vehicle trajectory prediction model using a combined framework of LSTM and MDN. Based on the fifth-order Bessel curve and constant speed/acceleration methods, candidate trajectory clusters for lane changing and lane keeping of the vehicle were generated, and a conversion model using improved TTC and TH indices was developed to quantify the collision risk for different vehicle interaction modes. Ammoun et al. [88] built a Kalman linear filter for trajectory prediction based on vehicle position, velocity, and acceleration and used a combination of circles to represent the spatial position occupied by the vehicle trajectories. The collision risk was finally evaluated according to the number of circles involved in the possible collision, the predicted collision duration, and the possible collision position.

The advantage of a risk assessment method based on spatiotemporal proximity is that it can quickly assess the risk state and improve computational efficiency. However, due to the relatively strong assumptions made for the spatiotemporal proximity index (as discussed in Section 4.1), the uncertainties of surrounding vehicles are hardly fully considered, which limits the application scenarios of this type of evaluation method [58,89].

(3) Risk evaluation based on uncertainty of multi-vehicle interaction

Considering different sources of uncertainty in characterizing the multi-vehicle interaction, including uncertainty in interaction behaviors, uncertainty in model parameters, and uncertainty in predicted trajectories, trajectory prediction-based risk assessment methods can be further divided into three categories accordingly. Among them, multi-vehicle interaction uncertainty refers to the uncertainty in determining the driving intention of surrounding vehicles, model parameter uncertainty refers to the inability to directly determine the relevant control parameters of the vehicle motion model, and predicted trajectory uncertainty refers to the overall uncertainty of trajectory prediction results in the predicted time domain.

a. Uncertainty in multi-vehicle interaction behaviors

When considering the uncertainty in driving behavior for risk assessment, it is necessary to first predict the driving intention of the surrounding vehicles to determine whether they will keep or change lanes. Joo et al. [90] constructed virtual lane-changing scenarios based on the historical maneuvers of the front and rear vehicles on both the original and target lanes and developed a multivariate Bayesian time series model to predict the future driving behavior of adjacent vehicles. The potential lane-changing risk was finally evaluated based on the safety evaluation results of the virtual scenarios. Huang et al. [91] established an Intention Identification Model (IIM) using an LSTM network to predict the driving intentions of the six vehicles around the subject vehicle and developed a Safety Field-Based Risk Assessment Model (RAM) to evaluate their potential risks. A comprehensive risk assessment model combining IIM and RAM was finally established to obtain a dynamic potential risk map considering multi-vehicle interaction. Liu et al. [92] proposed a leading-following vehicle game controller (LFGC), which modeled the interaction between the subject vehicle and surrounding vehicles as a partially observable vehicle gaming process, based on which the driving intentions and future trajectories of the surrounding vehicles were estimated in real time. These estimated trajectories were finally compared with the Model Predictive Control (MPC) based planned trajectory of the subject vehicle to determine the collision risk probability.

This kind of method is capable of considering the interaction behavior among multiple vehicles, offering a closer representation of real-world traffic scenarios and yielding more precise evaluation results. Nevertheless, in scenarios with numerous research vehicles, the computational complexity escalates, necessitating substantial computational resources. Additionally, this method is contingent upon the accurate modeling of vehicle interaction behavior, thus imposing a high demand on the behavioral data and model accuracy.

b. Uncertainty in model parameters

In order to obtain accurate future driving trajectories of vehicles, it is usually necessary to assume the probability distribution of motion parameters such as acceleration and steering angle in the vehicle motion model, and the simplest way is to assume a uniform distribution. Joerer et al. [93] assumed that the acceleration of a vehicle follows a uniform probability distribution. Based on the maximum deceleration and acceleration of the vehicle, the vehicle trajectory boundary was obtained, and the collision probability of each trajectory within the trajectory boundary was calculated. The overall collision risk of the driving scenario was finally estimated by integrating the collision probabilities of all trajectories. To improve the accuracy of risk assessment, some researchers have chosen Gaussian mixture method to establish the distribution models of the motion control parameters. Jasour et al. [94] used deep neural networks (DNNs) to predict the mean and covariance matrices of the motion control parameters under a Gaussian mixture distribution, based on which the nonlinear Chebyshev inequality and sum of squares (SOS) programming were employed to evaluate the overall driving risk.

This kind of method incorporates consideration for the uncertainty of model parameters and enhances the precision of evaluation results. However, achieving accurate model parameter estimation relies on meticulous parameter estimation methods. Inaccuracies in the estimation of model parameters can lead to substantial deviations in the evaluation results.

c. Uncertainty in predicted trajectories

Due to the complexity and uncertainty of the multi-vehicle interaction behaviors, analyzing the uncertainty of the predicted trajectories can be critical to improving the accuracy of the risk assessment results. Wang et al. [95] modeled the interaction behaviors among the vehicles within 30 m of the subject vehicle as a graph structure, based on which a trajectory prediction model was constructed using graph neural networks. Deep integration technology was further employed to train multiple prediction models and finally output a Gaussian distribution of the future trajectories (including their means and standard deviations) to quantify the future uncertain risks. Wang et al. [96] proposed a two-stage multimodal trajectory prediction model (P-PDRF), in which the first stage output is the predicted driving intention of the vehicle (lane changing or keeping), and the second stage output is the binary normal distribution of the predicted positions of the target vehicle (including the mean, variance, and correlation coefficients). Finally, the collision probability and expected collision severity given different driving intentions were obtained. Li et al. [97] constructed a vehicle trajectory prediction model using LSTM, whose output included the future trajectories of the six vehicles surrounding the subject vehicle as well as their error distributions, based on which Monte Carlo simulation was finally employed to evaluate the overall collision probability.

This kind of method enhances the reliability of evaluation results by accounting for the uncertainty in the mean distribution of the predicted trajectories. Nevertheless, the prediction model might not encompass unconventional situations, such as emergencies, potentially leading to inaccuracies in the evaluation results for abnormal scenarios.

In sum, compared with evaluation methods based on state inference, evaluation methods based on trajectory prediction results generally have higher computational costs; however, thanks to the comprehensive consideration of the spatial distribution relationship among all interacted vehicles in the future, their risk assessment results tend to be more accurate for multi-vehicle interaction scenarios. In addition, as a larger scope of interaction uncertainties is taken into account, trajectory prediction-based methods generally have a longer prediction horizon and can detect collision risks earlier.

5. Discussion

As summarized in Sections 2–4, although there have been many studies on risk assessment methods, there still exist shortcomings and challenges, especially for complex multi-vehicle interaction scenarios. The main challenges and future research trends can be summarized into the following aspects:

(1) Challenge 1: Assessing the risk of multi-vehicle interaction scenarios given incomplete environment information.

Compared with the ideal two-vehicle scenarios, risk assessment of multi-vehicle interaction scenarios often requires collecting a larger amount of environmental information data (describing the interaction behaviors of the subject vehicle and all of its surrounding vehicles). Most existing risk assessment methods assume that the required data are readily available in the Internet of Things environment. However, in real multi-vehicle scenarios, these data can be difficult to obtain for all interacting vehicles due to the limitations of sensor performance or blind spots, making it impossible to accurately assess the vehicle interaction risks [98]. In the future, more advanced networking technologies and fusion technologies are needed to retrieve comprehensive information data in real time for multi-vehicle interaction scenario risk assessment.

(2) Challenge 2: Improving the robustness of multi-vehicle interaction risk assessment methods.

Robustness can be used to evaluate the performance stability of risk assessment methods in scenarios that deviate from the original assumptions. Most existing risk assessment methods are implemented based on certain assumptions, such as the constant speed (acceleration) assumption, Gaussian distribution assumption of the vehicle motion/control parameters, etc. However, the actual multi-vehicle interaction scenarios can be complex and diversified, many of which may not conform to the predefined assumptions [99,100]. Once such scenarios occur, the accuracy of the risk assessment results can be questionable and needs further validation. In the future, it is necessary to further weaken the assumptions used in risk assessment or propose specific risk assessment methods for the targeted situations that do not meet the assumptions.

(3) Challenge 3: Verification of the effectiveness of multi-vehicle interaction risk assessment results.

The existing validation experiments often overlook the uncertainties of vehicle motion and interaction scenarios, making it difficult to accurately verify the effectiveness of the assessment methods/models for real-world practice. Also, as the true value of risk is impossible to obtain, the accuracy of the calculated risk values is difficult to testify. Expert scoring can be utilized to substitute the true value of risk and test the accuracy of risk assessment results by analyzing the consistency between the expert scores and the estimated risk values. However, this may be influenced by the subjective factors of the experts. In order to better evaluate the effectiveness of risk assessment methods, further research is needed to improve experiment design as well as to determine the "true value" of risks for multi-vehicle interaction.

(4) Challenge 4: Determination of the scope of interacting vehicles for multi-vehicle risk assessment.

The scope of interacting vehicles is rarely defined in the existing literature for multi-vehicle scenarios, that is, there is no clear spatial or temporal indicator to determine the number of surrounding vehicles that should be taken into account when assessing multi-vehicle interaction risk. If the scope is too large, too much manpower and material resources will be wasted, and the research question can be too complex to solve; on the contrary, there may be errors in the research results. Some studies select the surrounding vehicles into the research scope based on spatial indicators such as the distance from the subject vehicle, but these indicators are relatively simple and not necessarily suitable for multi-vehicle scenarios. A universally applicable method to determine the scope of interacting vehicles is urgently needed for multi-vehicle interaction risk assessment.

(5) Challenge 5: Identifying and including more factors affecting the risk of multi-vehicle interaction.

At present, most risk assessment methods for multi-vehicle interaction assume an ideal driving environment. Future research methods need to incorporate more driving risk influencing factors (such as drivers' personality and driving style, different weather conditions, lane geometry, more complex dynamic traffic participants, and specific traffic rules) into the feature set to improve the accuracy and effectiveness of the prediction models for multi-vehicle interaction risk.

6. Conclusions

In response to the key and difficult problem of safety situation assessment in multi-vehicle interaction scenarios, this article summarized the existing literature on the relevant data collection methodologies and vehicle interaction mechanism, based on which the existing multi-vehicle interaction risk assessment methods were systematically sorted out and classified, mainly including state inference-based methods and trajectory prediction-based methods. The application advantages and limitations of these methods in multi-vehicle interaction scenarios were analyzed, and the challenges and future trends of the field were discussed and summarized. In the future, more literature collection and analysis methods (such as clustering knowledge graphs) can be explored to provide a more comprehensive understanding of the research hotspots and development trends of risk assessment in multi-vehicle interaction scenarios.

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Nomenclature

TTC	Time to Collision
PET	Post Encroachment Time
SSM	Surrogate Safety Measures
TET	Time Exposed Time-to-Collision

TIT	Time Integrated Time-to-Collision
MTTC	Modified Time-to-Collision
H	Headway
TAdv	Time Advance
SDI	Stop Distance Index
PICUD	Potential Index for Collision with Urgent Deceleration
DSS	Difference of Space distance and Stopping distance
DRAC	Deceleration Rate to Avoid the Crash
CPI	Crash Potential Index
CFI	Conflict index
DBNs	Dynamic Bayesian networks
APF	Artificial potential field
PDRF	Probabilistic driving risk field
LSTM	Long Short-Term Memory
MDN	Mixed Density Networks
KF	Kalman Filter
IIM	Intention Identification Model
RAM	Risk Assessment Model
LFGC	Lading-following vehicle game controller
MPC	Model Predictive Control
DNNs	Deep neural networks
SOS	Sum of squares
P-PDRF	Predicted probabilistic driving risk field

References

1. Lefèvre, S.; Vasquez, D.; Laugier, C. A survey on motion prediction and risk assessment for intelligent vehicles. *ROBOMECH J.* **2014**, *1*, 1. [CrossRef]
2. Muzahid, A.J.M.; Kamarulzaman, S.F.; Rahman, M.A.; Murad, S.A.; Kamal, A.S.; Alenezi, A.H. Multiple vehicle cooperation and collision avoidance in automated vehicles: Survey and an AI-enabled conceptual framework. *Sci. Rep.* **2023**, *13*, 603. [CrossRef] [PubMed]
3. Li, Y.; Li, K.; Zheng, Y.; Morys, B.; Pan, S.; Wang, J. Threat assessment techniques in intelligent vehicles: A comparative survey. *IEEE Intell. Transp. Syst. Mag.* **2020**, *13*, 71–91. [CrossRef]
4. Zhu, S.; Jiang, R.; Wang, H.; Zou, H.; Wang, P.; Qiu, J. Review of Research on Traffic Conflict Techniques. *China J. Highw. Transp.* **2020**, *33*, 15–33.
5. Xiong, L.; Wu, J.; Xing, X.; Wu, X.; Chen, J. A Survey of Driving Risk Assessment for Autonomous Vehicles. *Chin. J. Automot. Eng.* 2023. Available online: http://kns.cnki.net/kcms/detail/50.1206.U.20230425.0916.002.html (accessed on 22 November 2023).
6. Ahmed, M.M.; Khan, N.; Das, A.; Dadvar, S.E. Global lessons learned from naturalistic driving studies to advance traffic safety and operation research: A systematic review. *Accid. Anal. Prev.* **2022**, *167*, 106568. [CrossRef]
7. Arun, A.; Haque, M.; Washington, S.; Sayed, T.; Mannering, F. A systematic review of traffic conflict-based safety measures with a focus on application context. *Anal. Methods Accid. Res.* **2021**, *32*, 100185. [CrossRef]
8. Jo, Y.; Oh, C.; Kim, S. Estimation of heavy vehicle-involved rear-end crash potential using WIM data. *Accid. Anal. Prev.* **2019**, *128*, 103–113. [CrossRef] [PubMed]
9. Wu, J.; Xu, H.; Zheng, Y.; Tian, Z. A novel method of vehicle-pedestrian near-crash identification with roadside LiDAR data. *Accid. Anal. Prev.* **2018**, *121*, 238–249. [CrossRef]
10. Wang, C.; Xia, J.; Lu, Z.; Qian, Z. Safe Evaluation Method Based on Traffic Simulation and Extreme Value Theory. *China J. Highw. Transp.* **2018**, *31*, 288–295. [CrossRef]
11. Papadoulis, A.; Quddus, M.; Imprialou, M. Evaluating the safety impact of connected and autonomous vehicles on motorways . *Accid. Anal. Prev.* **2019**, *124*, 12–22. [CrossRef]
12. Wang, Y.; Han, Z.; Xing, Y.; Xu, S.; Wang, J. A Survey on Datasets for Decision-making of Autonomous Vehicle. *arXiv* **2023**, arXiv:2306.16784.
13. Sun, P.; Kretzschmar, H.; Dotiwalla, X.; Chouard, A.; Patnaik, V.; Tsui, P.; Guo, J.; Zhou, Y.; Chai, Y.; Caine, B.; et al. Scalability in perception for autonomous driving: Waymo open dataset. In Proceedings of the 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, USA, 13–19 June 2020; pp. 2446–2454.
14. Yan, Z.; Sun, L.; Krajnık, T.; Ruichek, Y. Eu long-term dataset with multiple sensors for autonomous driving. In Proceedings of the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Las Vegas, NV, USA, 24 October 2020–24 January 2021; IEEE: New York, NY, USA, 2020; pp. 10697–10704.
15. Udacity. Public Driving Dataset. Available online: https://www.udacity.com/self-driving-car (accessed on 1 June 2023).
16. Binas, J.; Neil, D.; Liu, S.-C.; Delbruck, T. Ddd17: End-to-end davis driving dataset. *arXiv* **2017**, arXiv:1711.01458.

17. Huang, X.; Cheng, X.; Geng, Q.; Cao, B.; Zhou, D.; Wang, P.; Lin, Y.; Yang, R. The apolloscape dataset for autonomous driving. In Proceedings of the 2018 IEEE Conference on Computer Vision and Pattern Recognition Workshops, Salt Lake City, UT, USA, 18–22 June 2018; pp. 954–960.
18. Caesar, H.; Bankiti, V.; Lang, A.H.; Vora, S.; Liong, V.E.; Xu, Q.; Krishnan, A.; Pan, Y.; Baldan, G.; Beijbom, O. Nuscenes: A multimodal dataset for autonomous driving. In Proceedings of the 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, 13–19 June 2020; pp. 11621–11631.
19. Kovvali, V.G.; Alexiadis, V.; Zhang, L. Video-based vehicle trajectory data collection. In Proceedings of the Transportation Research Board 86th Annual Meeting, Washington DC, USA, 21–25 January 2007. 07-0528.
20. Yao, Y.; Wang, X.; Xu, M.; Pu, Z.; Atkins, E.; Crandall, D. When, where, and what? A new dataset for anomaly detection in driving videos. *arXiv* **2020**, arXiv:2004.03044,.
21. Zhang, F.; Wang, C.; Wang, J. Vehicle Interaction Patterns at On-ramp Merging Area of Urban Expressway. *China J. Highw. Transp.* **2022**, *55*, 66–79.
22. Zheng, L.; Sayed, T.; Mannering, F. Modeling traffic conflicts for use in road safety analysis: A review of analytic methods and future directions. *Anal. Methods Accid. Res.* **2021**, *29*, 100142. [CrossRef]
23. Arun, A.; Haque, M.; Bhaskar, A.; Washington, S.; Sayed, T. A systematic mapping review of surrogate safety assessment using traffic conflict techniques. *Accid. Anal. Prev.* **2021**, *153*, 106016. [CrossRef]
24. Zheng, L.; Sayed, T. From univariate to bivariate extreme value models: Approaches to integrate traffic conflict indicators for crash estimation. *Transp. Res. Part C Emerg. Technol.* **2019**, *103*, 211–225. [CrossRef]
25. Shi, Y.; Neubrand, A.; Koch, D. Characterization of Hardness and Stiffness of Ceramic Matrix Composites through Instrumented Indentation Test. *Adv. Eng. Mater.* **2019**, *21*, 1800806. [CrossRef]
26. Wang, Y.; Fang, Z.; Jian, Z.; Tu, Z.; Shi, N. Effects of Vehicle Load Characteristics on Distributions of Time-to-collision. *J. Transp. Syst. Eng. Inf. Technol.* **2020**, *20*, 240–246. [CrossRef]
27. Liu, K.; Jia, J.; Liu, C.; An, T. Warninh Effectiveness of Vehicle-to-infrastructure Cooperative Crossing Collision Prevention System at Non-signal Controlled Intersection. *China J. Highw. Transp.* **2018**, *31*, 222–230. [CrossRef]
28. Zhao, Y.; Zhang, S.; Ma, Z. Analysis of Traffic Accident Severity on Highway Tunnels Using the Partial Proportion Odds Model. *China J. Highw. Transp.* **2018**, *31*, 159–166.
29. Niu, Y.; Li, Z.; Fan, Y. Correlation Analysis of Influencing Factors of Truck Traffic Accidents on Expressways. *Saf. Environ. Eng.* **2020**, *27*, 180–188.
30. Yi, Z.; Li, W.; Shi, B.; Wang, B. An Impact Analysis of the Proportion of Adaptive Cruise Control Vehicles on the Safety of Mixed Traffic Flow at the Off-ramp Diverging Area. *J. Transp. Inf. Saf.* **2022**, *40*, 10–19.
31. Wu, B.; Wang, W.; Li, L.; Liu, Y. Longitudinal control model for connected autonomous vehicles influenced by multiple preceding vehicles. *J. Traffic Transp. Eng.* **2020**, *20*, 184–194.
32. Long, K.J.; Zhang, Y.; Zou, Z.Y.; Gu, J.; Hao, W. Vehicle and Non-motorized Vehicle Traffic Conflict Recognition at Signalized Intersection Based on Vehicle Trajectory. *J. Transp. Syst. Eng. Inf. Technol.* **2021**, *21*, 69–74. [CrossRef]
33. Ying, R.; Wen, H.; Zhao, S. Study on Driving Risk Measurement for Two-lane Freeway Vehicle Group. *J. Chongqing Jiaotong Univ. Nat. Sci.* **2019**, *38*, 95–100. [CrossRef]
34. Wang, J.; Xiong, H.; Xu, L.; Yan, X.; Guo, K. Mixed distribution model of modified time-to-collision considering risk levels in vehicle-to-vehicle communication. *J. Harbin Inst. Technol.* **2021**, *53*, 53–61.
35. Wang, B.; Gao, L.; Juan, Z. Analysis of Lane Changing Conflict Based on TTA in Expressway Weaving Area. *J. Syst. Simul.* **2018**, *30*, 3306–3311. [CrossRef]
36. Arun, A.; Haque, A.; Bhaskar, A.; Washington, S.; Sayed, T. A bivariate extreme value model for estimating crash frequency by severity using traffic conflicts. *Anal. Methods Accid. Res.* **2021**, *30*, 3306–3311. [CrossRef]
37. Ji, X.; Geng, Z. Bivariate Traffic Conflict Extreme Value Model of Truck Collision Prediction on Two-lane Mountain Highway. *J. Transp. Syst. Eng. Inf. Technol.* **2022**, *22*, 230–238. [CrossRef]
38. Zhang, L.; Zhao, K. Short-term Traffic Flow Risk Prediction on Freeways Based on Truck Factors. *J. Tongji Univ. Nat. Sci.* **2018**, *282*, 208–214.
39. Li, Z.; Yang, Z.; Liao, Y.; Yu, N.; Wu, Z.; Xie, H.; Shi, J.; Zeng, X. A Survey of Recent Advances in Data-Driven Event Prediction Research. *J. Cyber Secur.* **2022**, *7*, 40–55.
40. Sun, Z.; Fang, S. Vehicle Motion Pattern Analysis Method for Traffic Conflict Discrimination. *J. Tongji Univ. Nat. Sci.* **2017**, *45*, 839–846.
41. Qi, G.; Liu, S.; He, Y.; Wang, M.; Cao, A. Simulation-driven Based Utility Evaluation and Recommendation of Expressway Proactive Speed Limit. *J. Syst. Simul.* **2022**, *34*, 2522–2534. [CrossRef]
42. Shangguan, Q.; Fu, T.; Wang, J.; Jiang, R.; Fang, S. Quantification of Rear-End Crash Risk and Analysis of Its Influencing Factors Based on a New Surrogate Safety Measure. *J. Adv. Transp.* **2021**, *2021*, 5551273. [CrossRef]
43. Rahman, M.S.; Abdel-Aty, M. Longitudinal safety evaluation of connected vehicles' platooning on expressways. *Accid. Anal. Prev.* **2018**, *117*, 381–391. [CrossRef] [PubMed]
44. Oh, C.; Park, S.; Ritchie, S.G. A method for identifying rear-end collision risks using inductive loop detectors. *Accid. Anal. Prev.* **2006**, *38*, 295–301. [CrossRef]

45. Damani, J.; Vedagiri, P. An investigation of following behavior and associated safety of MTWs in heterogeneous traffic. *Transp. Lett.* **2023**, *5*, 1–13. [CrossRef]
46. Abdel-Aty, M.; Wang, Z.; Zheng, O.; Abdelraouf, A. Advances and applications of computer vision techniques in vehicle trajectory generation and surrogate traffic safety indicators. *Accid. Anal. Prev.* **2023**, *191*, 107191. [CrossRef]
47. Wang, C.; Xie, Y.; Huang, H.; Liu, P. A review of surrogate safety measures and their applications in connected and automated vehicles safety modeling. *Accid. Anal. Prev.* **2021**, *157*, 106157. [CrossRef]
48. Arun, A.; Haque, M.; Washington, S.; Sayed, T.; Mannering, F. How many are enough? Investigating the effectiveness of multiple conflict indicators for crash frequency-by-severity estimation by automated traffic conflict analysis. *Transp. Res. Part C Emerg. Technol.* **2022**, *138*, 103653. [CrossRef]
49. Zhao, X.; Wang, P.; Zhu, S.; Jiang, R.; Zou, H. Spatial Distribution of Traffic Conflicts in Interchange Merging Area Based on Video Recognition. *J. Highw. Transp. Res. Dev.* **2021**, *38*, 90–99.
50. Chen, S.; Ge, X.; Zhao, X.; Lu, J.; Xing, Y. Normal traffic risk assessment of second-class highways in mountainous areas during operation period. *China Saf. Sci. J.* **2022**, *32*, 176–183. [CrossRef]
51. Jiang, Y.; Hu, R.; Yao, Z.; Wu, P.; Luo, X. Stability and safety analysis for heterogeneous traffic flow composed of intelligent and connected vehicles. *J. Beijing Univ.* **2020**, *44*, 27.
52. Zou, H.; Liu, K.; Zhang, C.; Ma, R.; Wang, B. Study on Risk Evaluation of Truck Rear-end Collision in Continuous Downhill Section of Expressway. *J. Highw. Transp. Res. Dev.* **2022**, *16*, 92–101.
53. Han, L. Study on Traffic Conflict Discrimination and Safety Evaluation Model on Vehicle and Bicycle at The Signalized Intersection. Master's Thesis, Chang Gung University of Science and Technology, Taoyuan City, Taiwan, 2018.
54. Lin, Q. Modeling of Vehicle Collision Risk and Optimization of Lane-changing Strategy at Highway Diversion Area. *Sch. Transp. Southeast Univ.* **2020**.
55. Lan, L.; Xu, L.; Gong, Y. Evaluation of the conflict severity between pedestrians and right-turning vehicles. *J. Chongqing Univ. Technol. Nat. Sci.* **2020**, *36*, 70–77.
56. Wang, P.; Lu, J.; Xiang, Q. Research on Traffic Conflict Index of Highway Intersection. *Highway* **2008**, *12*, 128–131.
57. Brechtel, S.; Gindele, T.; Dillmann, R. Probabilistic decision-making under uncertainty for autonomous driving using continuous POMDPs. In Proceedings of the 2014 17th IEEE International Conference on Intelligent Transportation Systems, ITSC 2014, Qingdao, China, 8–11 October 2014; pp. 392–399. [CrossRef]
58. Tao, L.; Watanabe, Y.; Li, Y.; Yamada, S.; Takada, H. Collision Risk Assessment Service for Connected Vehicles: Leveraging Vehicular State and Motion Uncertainties. *IEEE Internet Things J.* **2021**, *8*, 11548–11560. [CrossRef]
59. Krajewski, R.; Bock, J.; Kloeker, L.; Eckstein, L. The highD Dataset A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems. *arXiv* **2018**, arXiv:1810.05642.
60. Chen, C.; Liu, L.; Qiu, T.; Ren, Z.; Hu, J.; Ti, F. Driver's intention identification and risk evaluation at intersections in the internet of vehicles. *IEEE Internet Things J.* **2018**, *5*, 1575–1587. [CrossRef]
61. Zhu, J.; Ma, Y.; Lou, Y. Multi-vehicle interaction safety of connected automated vehicles in merging area: A real-time risk assessment approach. *Accid. Anal. Prev.* **2022**, *166*, 106546. [CrossRef]
62. Katrakazas, C.; Quddus, M.; Chen, W.H. A new integrated collision risk assessment methodology for autonomous vehicles. *Accid. Anal. Prev.* **2019**, *127*, 61–79. [CrossRef] [PubMed]
63. Yang, K.; Wang, X.; Yu, R. A Bayesian dynamic updating approach for urban expressway real-time crash risk evaluation. *Transp. Res. Part C Emerg. Technol.* **2018**, *96*, 192–207. [CrossRef]
64. Wang, D.; Fu, W.; Song, Q.; Zhou, J. Potential risk assessment for safe driving of autonomous vehicles under occluded vision. *Sci. Rep.* **2022**, *12*, 4981. [CrossRef] [PubMed]
65. Elvik, R. A review of game-theoretic models of road user behaviour. *Accid. Anal. Prev.* **2014**, *62*, 388–396. [CrossRef] [PubMed]
66. Fukuyama, S. Dynamic game-based approach for optimizing merging vehicle trajectories using time-expanded decision diagram. *Transp. Res. Part C Emerg. Technol.* **2020**, *120*, 102766. [CrossRef]
67. Arbis, D.; Dixit, V.V. Game theoretic model for lane changing: Incorporating conflict risks. *Accid. Anal. Prev.* **2019**, *125*, 158–164. [CrossRef] [PubMed]
68. Chen, S. Lane-changing Trajectory Planning of Autonomous Vehicles Based on Risk Assessment in Mixed Driving Environment. Master's Thesis, Hefei University of Technology, Hefei, China, 2020.
69. Sheikh, M.S.; Wang, J.; Regan, A. A game theory-based controller approach for identifying incidents caused by aberrant lane changing behavior. *Phys. A Stat. Mech. Its Appl.* **2021**, *580*, 126162. [CrossRef]
70. Yu, H.; Tseng, H.E.; Langari, R. A human-like game theory-based controller for automatic lane changing. *Transp. Res. Part C Emerg. Technol.* **2018**, *88*, 140–158. [CrossRef]
71. Cai, Y.; Teng, C.; Xiong, X.; Wang, H.; Sun, X.; Liu, Q. Complex environment model, cognitive system and cognitive method of autonomous vehicle based on complex network. *CN Patent 113406955.* **2022**.
72. Chen, Y.; Deng, Y. Traffic Accident Risk Factor Identification Based on Complex Network. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *719*, 032074. [CrossRef]
73. Mohammadian, S.; Haque, M.; Zheng, Z.; Bhaskar, A. Integrating safety into the fundamental relations of freeway traffic flows: A conflict-based safety assessment framework. *Anal. Methods Accid. Res.* **2021**, *32*, 100187. [CrossRef]

74. Liu, T.; Li, Z.; Liu, P.; Xu, C.; Noyce, D.A. Using empirical traffic trajectory data for crash risk evaluation under three-phase traffic theory framework. *Accid. Anal. Prev.* **2021**, *157*, 106191. [CrossRef] [PubMed]
75. Khatib, O. Real-Time Obstacle Avoidance for Manipulators and Mobile Robots. *Int. J. Robot. Res.* **1986**, *5*, 90–98. [CrossRef]
76. Wang, J.; Wu, J.; Li, Y. Concept, Principle and Modeling of Driving Risk Field Based on Driver-vehicle-road Interaction. *China J. Highw. Transp.* **2016**, *13*, 44–50. [CrossRef]
77. Mullakkal-Babu, F.A.; Wang, M.; He, X.; van Arem, B.; Happee, R. Probabilistic field approach for motorway driving risk assessment. *Transp. Res. Part C Emerg. Technol.* **2020**, *118*, 102716. [CrossRef]
78. Wang, J. Intelligent Vehicle Collision Risk Assessment Based on Surrounding Vehicle Motion Prediction. Master's Thesis, Chongqing Jiaotong University, Chongqing, China, 2020.
79. Li, Y.; Wu, D.; Lee, J.; Yang, M.; Shi, Y. Analysis of the transition condition of rear-end collisions using time-to-collision index and vehicle trajectory data. *Accid. Anal. Prev.* **2020**, *144*. [CrossRef]
80. Shangguan, Q.; Fu, T.; Wang, J.; Luo, T.; Fang, S. An integrated methodology for real-time driving risk status prediction using naturalistic driving data. *Accid. Anal. Prev.* **2021**, *156*, 106122. [CrossRef]
81. Wang, X.; Zhang, X.; Guo, F.; Gu, Y.; Zhu, X. Effect of daily car-following behaviors on urban roadway rear-end crashes and near-crashes: A naturalistic driving study. *Accid. Anal. Prev.* **2022**, *164*, 106502. [CrossRef]
82. Khattak, Z.H.; Fontaine, M.D.; Li, W.; Khattak, A.J.; Karnowski, T. Investigating the relation between instantaneous driving decisions and safety critical events in naturalistic driving environment. *Accid. Anal. Prev.* **2021**, *156*, 106086. [CrossRef] [PubMed]
83. Orsini, F.; Gecchele, G.; Rossi, R.; Gastaldi, M. A conflict-based approach for real-time road safety analysis: Comparative evaluation with crash-based models. *Accid. Anal. Prev.* **2021**, *161*, 106382. [CrossRef] [PubMed]
84. Kovaceva, J.; Bärgman, J.; Dozza, M. On the importance of driver models for the development and assessment of active safety: A new collision warning system to make overtaking cyclists safer. *Accid. Anal. Prev.* **2022**, *165*, 106513. [CrossRef] [PubMed]
85. Groelke, B.; Earnhardt, C.; Borek, J.; Vermillion, C. A Predictive Command Governor-Based Adaptive Cruise Controller with Collision Avoidance for Non-Connected Vehicle Following. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 12276–12286. [CrossRef]
86. Ma, Y.; Zhu, J. Left-turn conflict identification at signal intersections based on vehicle trajectory reconstruction under real-time communication conditions. *Accid. Anal. Prev.* **2021**, *150*, 105933. [CrossRef] [PubMed]
87. Zhang, Y. Lane Change Risk Assessment and Decision Method Besed on Driving Style Identification and Motion Prediction. Master's Thesis, Xi'an University of Technology, Xi'an, China, 2020.
88. Ammoun, S.; Nashashibi, F. Real time trajectory prediction for collision risk estimation between vehicles. In Proceedings of the 2009 IEEE 5th International Conference on Intelligent Computer Communication and Processing, ICCP 2009, Cluj-Napoca, Romania, 27–29 August 2009; pp. 417–422. [CrossRef]
89. Zhang, L.; Xiao, W.; Zhang, Z.; Meng, D. Surrounding Vehicles Motion Prediction for Risk Assessment and Motion Planning of Autonomous Vehicle in Highway Scenarios. *IEEE Access* **2020**, *8*, 209356–209376. [CrossRef]
90. Joo, Y.J.; Park, H.C.; Kho, S.Y.; Kim, D.K. Reliability-based assessment of potential risk for lane-changing maneuvers. *Transp. Res. Rec.* **2021**, *2675*, 161–173. [CrossRef]
91. Huang, H.; Wang, J.; Fei, C.; Zheng, X.; Yang, Y.; Liu, J.; Wu, X.; Xu, Q. A probabilistic risk assessment framework considering lane-changing behavior interaction. *Sci. China Inf. Sci.* **2020**, *63*, 190203. [CrossRef]
92. Liu, K.; Li, N.; Tseng, H.E.; Kolmanovsky, I.; Girard, A. Interaction-Aware Trajectory Prediction and Planning for Autonomous Vehicles in Forced Merge Scenarios. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 474–488. [CrossRef]
93. Joerer, S.; Segata, M.; Bloessl, B.; Cigno, R.L.; Sommer, C.; Dressler, F. A vehicular networking perspective on estimating vehicle collision probability at intersections. *IEEE Trans. Veh. Technol.* **2014**, *63*, 1802–1812. [CrossRef]
94. Jasour, A.; Huang, X.; Wang, A.; Williams, B.C. Fast nonlinear risk assessment for autonomous vehicles using learned conditional probabilistic models of agent futures. *Auton. Robot.* **2022**, *46*, 269–282. [CrossRef]
95. Zhao, X.; Liu, J.; Zhu, S.; Zhu, L.; Wang, H.M. A Motion Planning Method for Autonomous Vehicles Considering Prediction Risk. *Automot. Eng.* **2023**, icca. [CrossRef]
96. Wang, X.; Alonso-Mora, J.; Wang, M. Probabilistic Risk Metric for Highway Driving Leveraging Multi-Modal Trajectory Predictions. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 19399–19412. [CrossRef]
97. Li, P.; Pei, X.; Chen, Z.; Zhou, X.; Xu, J. Human-like motion planning of autonomous vehicle based on probabilistic trajectory prediction. *Appl. Soft Comput.* **2022**, *118*, 108499. [CrossRef]
98. Hu, Y.; Li, Y.; Huang, H.; Lee, J.; Yuan, C.; Zou, G. A high-resolution trajectory data driven method for real-time evaluation of traffic safety. *Accid. Anal. Prev.* **2022**, *165*, 106503. [CrossRef]
99. Li, H.; Li, Y.; Zhen, T.; Li, H. Obstacle avoidance method for intelligent vehicle in complex environment. *CAAI Transactions on Intelligent Systems.* **2023**, 1–11.
100. Zhu, S.; Chang, H.; Jiang, R.; Wu, J.; Wang, H.; Liao, L. Identification of highway rear-end risk considering lane-changing behavior. *J. Wuhan Univ. Technol. Transp. Sci. Eng.* **2023**, *65*, 1–9.