



# **Review Research Progress and Prospects of Vehicle Driving Behavior Prediction**

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**Abstract:** Autonomous driving technology is vital for intelligent transportation systems. Vehicle driving behavior prediction is the foundation and core of autonomous driving. A detailed review of the existing research on vehicle driving behavior prediction can improve the understanding of the current progress of research on autonomous driving and provide references for follow-up researchers. This paper primarily reviews and analyzes the control models of autonomous driving, prejudgment methods, on-road and intersection traffic decision-making, and shortcomings of the research about the prediction of individual intelligent vehicle driving behavior, the prediction on movements of vehicles connected via the Internet, and prediction of driving behavior in a mixed traffic environment. The deficiencies in the research on vehicle driving behavior prediction are as follows: (1) there are numerous limitations in the intelligent application scenarios of individual intelligent vehicles; (2) although the Internet of Vehicles is a significant developmental trend, the training and test datasets are not rich enough; and (3) as the research of mixed traffic flow is still in the initial stages, the comfort brought by autonomous driving in hybrid driving environments is not being considered. In addition to the above analyses and comments, the future research prospects of vehicle driving behavior prediction are discussed as well.

**Keywords:** traffic engineering; intelligent transportation; autonomous vehicle; driving behavior; individual intelligent vehicle; Internet of Vehicles

# 1. Introduction

The rapid increase in car ownership in the last few years has led to a corresponding increase in traffic accidents. According to the World Health Organization (WHO), traffic accidents are one of the top ten causes of death globally. An accident report published by Volvo revealed that human error is the main cause in nearly 90% of all traffic accidents. Advanced driver assistance systems (ADASs) or autonomous vehicles (AVs) are considered to be effective solutions in reducing human error and the corresponding rate of traffic accidents.

Prejudgment of the vehicle driving intention and behavior is the basis of AVs and is the primary focus of scholars in related fields. Depending on whether the vehicle interacts with roadside infrastructure and other vehicles, autonomous driving vehicles can be divided into two groups: individual intelligent vehicles and the Internet of Vehicles (IoV). As the degree of intelligence and automation of vehicles in actual traffic is uneven, the recognition and prediction of vehicle driving behavior in various traffic environments have become key considerations in the development of IoV and AVs.

Several studies on driving behavior prediction have been conducted in recent years, using methods such as support vector machines, Markov chains, neural networks, Bayesian methods, and game theory. These methods are based on a wide variety of disciplines, including computer science, mathematics, economics, and physics. The models used in these methods range from rule-based models to learning algorithm models and from one-sided description models to specific functional models. However, most models are based



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**Copyright:** © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). on individual intelligent vehicles. The advantages offered by IoV are not exploited, and mixed traffic driving environments are often ignored.

This paper reviews research on individual intelligent vehicle driving behavior prediction, IoV driving behavior prediction, and driving behavior prediction in mixed traffic driving environments to obtain a detailed understanding of the current progress of research on vehicle driving behavior prediction, which is an important subset of AV control challenges. The contribution of this paper is twofold. At first, we explore the different driver behavior prediction models. The results show that IoV has more advantages. The second contribution is about the prospects of AVs.

In this paper, Section 2 introduces individual intelligent vehicles, Section 3 presents a discussion of the IoV driving behavior, and Section 4 explores mixed traffic driving.

## 2. Research on Individual Intelligent Vehicle Driving Behavior Prediction

The original definition of an AV is an individual intelligent vehicle that relies on recognizing the behavior of surrounding vehicles to predict their short-term trajectories and then makes reasonable driving plans, such as staying in lane or changing lanes, using algorithms, models, functions, and other methods.

#### 2.1. Individual Intelligent Vehicle Motion-Planning Model

The global positioning of AVs is realized by an onboard GPS, and local path planning is completed by a motion-planning model.

Numerous scholars have systematically reviewed predictive decision-making models of individual intelligent vehicle behavior. Thomas et al. [1] reviewed the research results of an AV behavior decision-making system, compared and analyzed the research progress of various behavior models, and emphasized the importance of driving behavior analysis. Kumar and Prasad [2] divided driving behavior models into analysis models and prediction models, compared and analyzed numerous models in detail, and showed that driver behavior models significantly differ from different vehicle drivers. Xiong et al. [3] divided driving behavior decision models into two types of models, namely rule-based and learning algorithm-based models; they affirmed the superiority of the latter. In contrast, Chen et al. [4] proposed a novel system based on the combined research results of the two kinds of driving behavior models: descriptive models and functional models. They revealed that existing descriptive models are too one-sided and functional models lack reliable big data support, making them unsuitable for the complex traffic environments found in China.

Recently, machine learning has been widely employed in the field of driver behavior recognition, particularly by Tesla, which, based on camera visual perception, uses artificial intelligence and data learning to perform behavior prediction and trajectory planning.

Berndt et al. [5] used the hidden Markov model (HMM) to recognize driving intentions. Zhu et al. [6] and Zhang et al. [7] proposed a driving behavior recognition method based on a support vector machine (SVM); the test results demonstrated a good recognition effect. Liu et al. [8] integrated the HMM and SVM methods to improve the accuracy of driving intention recognition. Considering a case with an insufficient sample dataset for machine learning, Zong et al. [9] proposed a driver behavior prediction model based on the HMM and an artificial neural network (ANN), which uses the HMM to tutor the ANN to improve learning. An experiment proved that multiview convolutional neural network (MV-CNN) and joint data augmentation (JDA) have better generalization ability than ANN [10].

Although a machine learning classification algorithm can identify the intention of a driver to change lanes to the left or right lane or stay in the current lane, it cannot provide a specific driving trajectory. Consequently, Ye et al. [11] used a kinematic or dynamic model to predict vehicle trajectory. Hu et al. [12] proposed an AV path planning method based on discrete optimization.

Ji et al. [13] believed that trajectory and driving intention should be predicted simultaneously. Therefore, they used deep learning methods to design a driving intention recognition and vehicle trajectory prediction model based on a long short-term memory (LSTM) network. The proposed model significantly improved the accuracy of intention recognition and trajectory prediction of the surrounding vehicles.

#### 2.2. Prediction of Individual Intelligent Vehicle Behavior Recognition

## 2.2.1. Prediction of Individual Intelligent Vehicle Driving Behavior on Roads

On-road driving can be divided into straight and lane-changing driving behaviors. Both behaviors must be accurately predicted and judged by AVs to ensure smooth and safe driving in continuous traffic flow.

Adaptive cruise control (ACC) is used to detect and track the vehicle ahead and maintain a safe and comfortable distance. The concept of car-following is implemented based on this technology. ACC is one of the most important technologies for AVs. It improves driving comfort, reduces driver error, improves safety, increases traffic capacity, and reduces fuel consumption. Numerous scholars have conducted detailed research on ACC. Zhu et al. [14] calibrated the response time parameters between vehicles based on the experience of skilled drivers and proposed an ACC control strategy based on response time to improve the safety and reliability of the system. Zhu et al. [15] used deep reinforcement learning theory to optimize car-following control in ACC. Luo et al. [16] proposed a multiobjective ACC algorithm based on a model predictive control (MPC) framework that significantly improved driving comfort and fuel economy.

Compared to straight driving, lane-changing behavior can be dangerous and cause serious accidents, primarily due to the inaccurate estimation of the surrounding traffic. Extensive research has been conducted on lane-change control systems to alleviate this problem. Chen et al. [17] combined rough set methods to propose lane-changing rules for AVs in an urban environment. Jiang et al. [18] determined an optimal lane-changing trajectory based on the hp-adaptive pseudospectral method and manual driving trajectory and established lane-changing rules for AVs in emergency situations. From the perspective of machine learning, dynamic Bayesian networks [19,20] and random forest methods [21] have also been widely used to intelligently predict the trajectory of a vehicle lane-changing maneuver.

#### 2.2.2. Prediction of Individual Intelligent Vehicle Driving Behavior at Intersections

Road intersections are vital for traffic movement and are required for vehicles to gather, turn, and evacuate. Safe and efficient passing through intersections is an important area of research for AVs. As individual intelligent vehicles cannot interact with other vehicles and achieve collaborative control, they cannot rely solely on motion models to pass through complex intersections. Song et al. [22] stated that AVs must understand the driving intentions of human drivers, and they proposed an intention decision-making algorithm to ensure that AVs can pass through intersections intelligently. In contrast, Cheng et al. [23] used a different approach and believed that purely probabilistic or evidence-based techniques were not sufficiently effective tools for such decision-making. They suggested that game theory tools can better judge and recognize the evolution of uncertain situations, and they proposed a game model for AVs driving through intersections with both manned and unmanned vehicles.

Unsignalized intersections (USI) also are challenging for AVs due to high uncertainties. Yang et al. [24] identified multiple impact variables of AVs at USI using a random forest approach.

# 2.3. Research Comments

#### 1. Individual intelligent vehicle motion-planning model

The rule-based behavior decision system represented by the finite state machine is widely used in the DARPA Urban Challenge. However, methods such as convolutional neural networks and deep learning based on learning algorithms rely too much on the richness and accuracy of training data; nevertheless, Kumar, Xiong, and Chen believed that they have significant potential in the field of autonomous driving.

Considering the research on behavior prediction and decision-making, the introduction of machine learning and other technologies to intelligent vehicle control, such as in the models proposed by Berndt, Zhu, Liu, and other scholars, appears to be a general trend. However, the extraction and collection of learning data must be considered. Considering the field of machine learning, classification algorithms can better identify driving intentions, regression algorithms can effectively extrapolate driving trajectories, and clustering algorithms can be used to analyze driving styles.

The individual intelligent vehicle models listed in Table 1 were all developed toward personalized and intelligent fully automated driving, as shown in Figure 1. Owing to the upper limit of the ability of individual intelligent vehicles, current AVs are limited by various factors and require human intervention during driving. Automatic driving cannot be fully realized as there are significant differences between automatic driving and personal manual driving habits, and driving comfort is usually poor.

Table 1. Research summary of motion planning models for individual intelligent vehicles.

Research Objective	Author	Year	Opinion or Model
Review	Thomas [1]	1994	Emphasized the importance of driving behavior analysis
	Kumar et al. [2]	2015	Driver behavior models significantly differ for different vehicle drivers
	Chen et al. [4]	2016	Believed that functional models are superior to descriptive models
	Xiong et al. [3]	2018	Based on the potential of the learning algorithm model
Intent recognition	Berndt [5] Zhu et al. [6] Liu et al. [8] Zong et al. [9] Zhang et al. [10] Zhang et al. [7]	2008 2017 2018 2009 2019 2021	Used HMM to recognize driving intention Recognition method of driving behavior based on SVM HMM and SVM Proposed HMM and ANN driver behavior prediction models MV-CNN has better generalization ability than ANN SVM optimization
Trajectory prediction	Ye et al. [11]	2016	Established dynamic model to predict vehicle trajectory
	Hu et al. [12]	2018	AV path planning method based on discrete optimization
	Ji et al. [13]	2019	Vehicle trajectory prediction model based on LSTM



Figure 1. Research course of motion planning model of individual intelligence.

## 2. Prediction of individual intelligent vehicle driving behavior on roads

The research on ACC systems, as shown in Figure 2 and Table 2, utilizes car control strategies based on factors such as reaction time or distance to ensure safety by maintaining a safe distance from the vehicle ahead. However, reaction time and safe distance are different for different drivers. Consequently, it is difficult to calibrate ACC systems, resulting in poor performance indicators such as comfort. The application of deep reinforcement learning theory and the MPC framework in intelligent transportation systems can improve the intelligence of ACC systems. Notably, most current ACC systems focus on analyzing the impact of longitudinal traffic flow and ignore the impact of lateral vehicles in complex urban traffic environments.



Figure 2. Structure chart of driving behavior prediction of individual intelligent vehicles.

Research Objective	Author	Year	Opinion or Model
Straight	Luo et al. [16]	2009	Improve driving comfort and fuel economy
	Zhu et al. [14]	2017	ACC strategy based on response time
	Zhu et al. [15]	2019	ACC car-following control optimization
Lane- changing	Schreier et al. [19] Toru et al. [20]	2014	Lane-changing probability of dynamic Bayesian network
	Schlechtriemen et al. [21]	2015	Prediction of lane-changing based on random forest method
	Chen et al. [17]	2017	Combining rough set urban environment lane-changing rules
	Jiang et al. [18]	2019	Autonomous driving emergency lane-changing rules
Intersections	Song et al. [22]	2016	Intention perception of driver at intersection
	Cheng et al. [23]	2019	Intersection driving game model
	Yang et al. [24]	2019	USI multiple impact variables

Table 2. Research summary of driving behavior prediction of individual intelligent vehicles.

Considering lane-changing behavior, as shown in Figure 2 and Table 2, current smart car lane-changing trajectory planning includes methods such as search, optimization, and functions. New methods, such as the hp-adaptive pseudospectral method and artificial

intelligence, use functional methods to overcome hysteresis and the redundancy of existing methods. However, the problem of imperfect data still persists. Moreover, the influence of lateral vehicles and the relative speed of the obstacles ahead must be considered. The combination of rough sets can increase the generality of lane-changing control algorithms but has limitations in terms of its accuracy.

3. Prediction of individual intelligent vehicle driving behavior at intersections

Traffic automation of individual intelligent vehicles at intersections is a complex problem. This is primarily because the traffic complexity at intersections is much higher than that of ordinary road sections. In general, only the intelligent motion planning model embedded in the vehicle is used, and its efficiency and safety are yet to be investigated. Song et al. proposed an intersection driver-intention perception decision-making algorithm, and Cheng et al. proposed a game theory model to optimize the traffic perception of individual intelligent vehicles at intersections. However, independent and one-sided approaches cannot be used to solve the problems of individual intelligent vehicles, and manual intervention is still required.

The discussed studies in the second section are summarized in Table 3.

Chapter	Researc	h Objective	Summary	Author/Year
	Review		Reviewed and analyzed driving behavior models from different perspectives	Thomas/1994 [1] Kumar et al./2015 [2] Chen et al./2016 [4] Xiong et al./2018 [3]
Individual intelligent vehicle motion-planning model	Intent recognition		The introduction of machine learning and other technologies to intelligent vehicle control	Berndt/2008 [5] Zhu et al./2017 [6] Liu et al./2018 [8] Zong et al./2009 [9] Zhang et al./2019 [10] Zhang et al./2021 [7]
	Trajectory prediction			Ye et al./2016 [11] Hu et al./2018 [12] Ji et al./2019 [13]
	On-road	Straight	Development and optimization of ACC	Luo et al./2009 [16] Zhu et al./2017 [14] Zhu et al./2019 [15]
Prediction of individual intelligent vehicle behavior recognition		Lane- changing	Safe and reliable lane-changing control systems are needed	Schreier et al./2014 [19] Toru et al./2014 [20] Schlechtriemen et al./ 2015 [21] Chen et al./2017 [17] Jiang et al./2019 [18]
	At intersections		Its efficiency and safety are yet to be investigated	Song et al./2016 [22] Cheng et al./2019 [23] Yang et al./2019 [24]

Table 3. Research summary of individual intelligent vehicle driving behavior prediction.

## 3. Research on IoV Driving Behavior Prediction

Tian Bin et al. [25] stated that cooperative vehicle infrastructure (CVI) and IoV are key technologies for overcoming the limitations of individual intelligence in AVs. The international standard for autonomous driving (ISAD) was proposed in 2019. This standard categorizes the facilities required to support autonomous driving into five levels, wherein the A-level defines roads that can enable autonomous driving, with AVs, roads, and traffic

connected by ISAD. IoV technology has gradually transitioned from individual intelligent vehicles to vehicle-to-vehicle (V2V) communication, data distribution, and CVI. IoV technology enables the formation of an organic vehicle–road–person entity.

## 3.1. IoV Model Optimization

Considering the shortcomings of the individual intelligent vehicle motion models, Li et al. [26] stated that an IoV environment should not only include "individual intelligence" driving, but also share environmental perception and driving decision information with other IoV vehicles and intelligent roadside infrastructures. Accordingly, a collaborative decision-making mechanism can be adopted to realize "networked intelligence" operations. Zhao et al. [27] proposed a multimodal multitask spatial-temporal convolution (MM-STConv) end-to-end autonomous driving behavior decision model. It is based on RGB images, deep learning, and vehicle history data [28], and can better predict the trajectory of the vehicle ahead to control its own speed and turning angle.

#### 3.2. Prediction of IoV Driving Behavior

# 3.2.1. Prediction of IoV Driving Behavior on Roads

An ACC system can be further optimized by IoV. Su et al. [29] and Jin [30] proposed a car-following model based on ACC that considers the behavior of the driver and studied the relationship between the longitudinal traffic flow in an IoV driving environment. Yang et al. [31] further studied the potential of ACC in IoV environments based on the car-following model. They revealed that a data-driven car-following model in a big data environment can rapidly adapt to changes in driving behavior and provide important support for the development of AVs.

Geng et al. [32] proposed an automatic driving lane-changing motion planning and control algorithm based on a priori probability and a posteriori deterministic prediction. The status quo of the surrounding environment and possible dangerous behaviors are considered simultaneously to determine whether the vehicle stays in its current lane or changes lanes. Huang et al. [33] and Tejada et al. [34] proposed an intelligent vehicle lane-changing trajectory planning and control system considering different driving styles. Based on historical data, they defined three driving styles: aggressive, ordinary, and cautious. Drivers with different styles were found to have different requirements for the use of intelligent vehicles.

The emergence of IoV has improved the intelligence and personalization of lanechanging control in AVs, and new research has been conducted to ensure the safety of lane-changing behavior. Huang et al. [35] proposed a driver behavior analysis method based on the vehicle onboard diagnostic (OBD) information and AdaBoost algorithms. It can better determine whether the current driving behavior belongs to safe driving or not. Bussooa et al. [36] proposed a system to monitor drivers using the Internet of Things (IoT) technology and regulate their lane-changing behavior. Wu et al. [37] and Zhang et al. [38] established an intelligent vehicle collision avoidance model that can reduce the collision risk of AVs during lane-changing, considering different perspectives. Xue et al. [39] proposed a method to recognize dangerous driving behavior and provide a reference for the risks posed by surrounding vehicles.

# 3.2.2. Prediction of IoV Driving Behavior at Intersections

IoV removes the barriers between individual vehicles and between vehicles and infrastructure. The prediction of driving behavior at intersections is an important area of study in autonomous driving research.

Xiong et al. [40] proposed a method to predict the driving intentions of other vehicles based on the HMM, which controls the motion behavior of intelligent vehicles through a hybrid state system. This method realizes the interactive problem of vehicles on a highway ramp and verifies the cooperative control of unmanned vehicles at intersections. Based on the development of vehicle-to-infrastructure (V2I) and V2V communications and historical driving data, Song et al. [41] and Duan et al. [42] proposed a behavioral decision model for intelligent vehicles and multivehicle collaborative control at intersections.

#### 3.3. Research Comments

1. IoV model optimization

The studies discussed in this section are summarized in Figure 3 and Table 4. These studies considered not only the influence of the driver of a single ICV on vehicle motion planning, but also the interactive influence of the decision-making of multiple ICVs. This represents a novel approach for the development of ICVs and fully autonomous driving technology. AVs cannot be completely individual intelligences, and each vehicle must be intelligent. Essentially, a system of "autonomous intelligence" + "connected intelligence" is required.

Table 4. Research summary of IoV driving behavior prediction.

<b>Research Objective</b>	Author Year		<b>Opinion or Model</b>		
Straight					
ACC car-following model	Jin [30] Su et al. [29] Yang et al. [31]	2011 2018 2019	Car-following model based on driver behavior Personalized car-following model Data-driven car-following model		
Lane-changing					
Lane-changing intention	Geng et al. [32] Huang et al. [33] Tejada et al. [34]	2015 2019 2020	A priori and a posteriori lane-changing prediction Trajectory planning and control based on driving style Based on models of 'typical' human driving behavior		
Lane-changing safety Huang et al. [35] Bussooa et al. [36] Wu et al. [37] Zhang et al. [38] Xue et al. [39]		2015 2019 2019 2020 2020	Behavior analysis method based on OBD Monitoring illegal lane-changing behavior using IoT Collision avoidance model based on vehicle contour AV high-speed collision avoidance model Dangerous vehicle marking		
Intersections					
Intersection	Xiong et al. [40]	2014, 2015	Intersection cooperative control method based on HMM		
cooperative control	Song et al. [41] Duan et al. [42]	2016 2020	Decision-making model for intersection behavior Multivehicle cooperative control based on V2I and V2V intersections		

Considering the MM-STConv end-to-end autonomous driving behavior decision model proposed by Zhao et al., the introduction of deep learning and networked historical data can solve the problem of a lack of a priori probability. Currently, some models rely on images to a significant extent. Poor weather conditions, low ambient brightness at night, and the reflections of the vehicles ahead can result in poor prediction results.

# 2. Prediction of IoV driving behavior on roads

The application of car-following models and data-driven car-following models in intelligent transportation systems in IoV environments can increase the intelligence of ACC systems. These models are based on nonparametric methods (artificial intelligence, machine learning, deep learning, etc.) and can adapt to the complex driving environments and aggressive driving behavior in China, but they require a large amount of high-precision data as a sample dataset.



Figure 3. Structure chart of IoV driving behavior prediction.

In contrast to independent real-time decision-making by individual intelligent vehicles, Geng et al. comprehensively considered the a priori probability of traffic rules, driving experience, and driver style and the HMM-based a posteriori probability to fully realize the advantages of IoV. This approach reduces the time required for behavior recognition and trajectory planning and improves the prediction accuracy. Based on the application of an intelligent rough set of individual intelligent vehicles, the consideration of driving personalization factors demonstrated by Huang et al. is important. The supplement of such factors not only realizes the personalized requirements of drivers with different driving styles, but also improves the algorithmic constraints on the basis of rough sets to ensure accurate control.

# 3. Prediction of IoV driving behavior at intersections

The intersection behavior decision model proposed by Song et al. and the multivehicle cooperative control model at intersections proposed by Duan et al. are considered as examples for further discussions. Using V2I and V2V technologies, the intersection traffic model can help AVs judge the traffic conditions of other vehicles at intersections and use dedicated short-range communication (DSRC) technology to realize multivehicle coordinated control at unsignalized intersections, which is in line with the development trend of coordinated vehicle–road development. The introduction of HMM, driver intention analysis, and other technologies can establish new research directions, enrich the research on autonomous driving at intersections, and improve the safety and comfort of driving behavior prediction in intermittent traffic flow.

As these models make driver judgments based on historical vehicle trajectory, without the influence of the other vehicles entering the intersection, the collected data are imperfect, and the judgment results have errors. Therefore, future research can use onboard networking equipment, sensors, and CAN or CIDAS data [43] to improve judgment accuracy.

# 4. Research on Predictive Problems in Mixed Traffic Driving Environments

#### 4.1. Research on Automatic–Manual Mixed Traffic Flow

Existing research generally assumes that AVs have a high level of intelligence and actual road traffic consists of mixed traffic flow, with different types of vehicles (such as automatic–manual mixed traffic flow). The study of mixed traffic flow reveals the internal

mechanism of real traffic and can help build more accurate and faster predictive models for AVs.

Research on mixed traffic flow comprising automatic and manual driving has gradually increased in recent years. Bose et al. [44] analyzed the influence of automatic–manual mixed traffic flow on the traffic flow characteristics and environment in a single lane. Subsequently, Ioannou et al. [45] analyzed same-scale automatic and manual driving traffic density maps and simulated the changing characteristics of mixed traffic flow. Huang et al. [46] proposed a method to enable the coexistence of AVs and manual vehicles, thereby reducing the cost of highway automation and infrastructure requirements. Qiu [47] proposed a traffic flow model for mixed flow with automatic and manual driving. Some scholars believe that if the proportion of intelligent vehicles reaches 80%, the traffic flow capacity would be twice that of fully manual driving, and traffic congestion would be reduced by 50% [48].

Research on mixed traffic flows has increased significantly in recent years. Qin et al. [49] analyzed the differences in traffic behavior between cooperative adaptive cruise control (CACC)/ACC vehicles and manually driven vehicles and combined their respective advantages and disadvantages to build a car-following model and establish a theoretical basis for heterogeneous traffic flow. Ye et al. [50–53] established a model for ICVs in mixed traffic flows based on a two-lane cellular automation model for heterogeneous traffic flows. Subsequently, they proposed a modeling method for ICVs based on the chart method and simulated the model considering factors such as density, speed, performance, and permeability.

# 4.2. Research Comments

As shown in Table 5, scholars have conducted extensive research on automatic-manual mixed traffic flow. Bose et al. and Ioannou et al. applied the Q-K diagram to illustrate that automated transportation improves transportation efficiency in a study on the importance of autonomous driving. Huang et al. proposed an autonomous vehicle driving system (AVDS) that only uses vehicle sensor information, thereby eliminating the need for communication between vehicles. This can help individual intelligence AVs to quickly enter the market, and it allows manual and automatic vehicles to coexist. Nevertheless, there are considerable shortcomings with individual intelligent vehicles, and communication between vehicles is necessary. Therefore, vehicles as part of an IoV system can better coexist with manual vehicles and individual intelligent vehicles.

Table 5. Research summary of IoV driving behavior prediction.

Author	Year	Opinion or Model
Bose et al. [44]	1999	Automatic-manual mixed traffic flow characteristics in a single lane
Huang et al. [46]	2000	Coexistence of AVs and manual vehicles
Ioannou et al. [45]	2003	Analyzed and studied automatic and manual driving Q-K diagrams
Qiu et al. [47]	2016	Mixed traffic flow model
Ye et al. [50–53]	2018	ICV modeling method in mixed traffic flow
Qin et al. [49]	2019	Car-following model of heterogeneous traffic flow

From another perspective, the above research showed that disruptions from manual vehicles would obviate the advantages of AVs. Accordingly, heterogeneous traffic flow theory becomes significant due to the difficulty of completely eliminating manual driving in a short time, which may better coordinate the mixed traffic flow.

The above-mentioned research primarily analyzes automatic–manual mixed traffic flow considering driving safety and efficiency. However, some studies also consider the mutual influence mechanism of automatic and manual driving, especially in a mixed traffic flow in an IoV environment. Ye et al. and Qin et al. explored the theoretical basis of the interaction mechanism of heterogeneous traffic flows.

# 5. Conclusions

## 5.1. Shortcomings

Several studies and experiments related to vehicle automation, in areas such as individual intelligence AVs, IoV, AVs, and mixed traffic flow driving behavior prediction, have been conducted in recent years. These research efforts have yielded invaluable knowledge and data, which have promoted the development of AVs.

A systematic review of the existing research was performed herein, which revealed that most traditional individual intelligent vehicle behavior prediction models are only suitable for specific traffic scenarios and cannot adapt to complex scenarios, such as complex intersections. Although the individual intelligent vehicles manufactured by companies such as Tesla use advanced artificial intelligence and machine learning algorithms, driving in dynamically changing traffic conditions remains a significant challenge for individual intelligent vehicles, especially on city roads. The collaborative control of vehicles belonging to an IoV network can help AVs make more accurate behavior predictions and more reasonable trajectory planning. However, the current data collection, analysis, and arrangement methods are not systematic, and training and test datasets are quite poor. Consequently, IoV technology is not yet suitable for widespread adoption.

Existing driving control algorithms primarily set path tracking accuracy as the main control target, leading to the frequent starting and stopping of vehicles. Consequently, AVs are more likely to cause motion sickness compared to traditional vehicles. In addition, the short reaction times and following distances of AVs can increase the psychological pressure on persons driving traditional vehicles, creating additional traffic safety hazards. This is even more prominent in current driving environments with mixed traffic flows.

Considering the prejudgment of vehicle driving behavior, there are numerous limitations in the application of individual intelligent vehicles that require the cooperation of specific traffic environments, thereby preventing the development of fully autonomous vehicles. The combination of IoV and AVs has several advantages, but the available training datasets are not rich enough. Despite being integrated with decision-making processes, the application of driving behavior prediction remains a significant challenge. Mixed traffic flow has gradually become an important area of research. Nevertheless, theoretical and applied research is still relatively rare, and the comfort of autonomous driving in a mixed driving environment is still poor.

## 5.2. Prospects

# 1. Recognition of driving status based on vehicle files

Owing to the relationship between the personality traits of a driver and their driving behavior, IoV can be used to establish a priori logic that considers the personality of the driver, vehicle history, traffic rules, etc. When driving on the road, other ICVs can obtain this logic by scanning the license plates of neighboring vehicles using onboard cameras. The a priori probability of the driving behavior of the vehicles can be calculated, and the dynamic Bayesian network or random forest method can be used to calculate the a posteriori probability and provide efficient and accurate behavior prediction and trajectory planning.

IoV and CVI can fully exploit the advantages offered by big data; together with vehicle driving history data, they can be used to identify the type of driver and provide personalized automatic driving control. Furthermore, deep learning algorithms and neural networks can be used to simulate the driving of experienced drivers in AVs, such that that the trajectory of autonomous driving satisfies the requirements of different drivers. In mixed traffic flow environments, different motion planning models are required based on the driving conditions and vehicles ahead, considering the degree of driving anthropomorphism and ride comfort, to satisfy safety requirements.

2. Realization of fully autonomous driving based on all-element traffic information perception

The "Automotive Driving Automation Classification" was formally implemented in China on 1 January 2021. It divides driving automation into six levels, i.e., Levels 0–5. Level 0–2 autonomous driving requires the driver to take over dynamic driving tasks during the entire process. Level 3 represents conditional autonomous driving, which is already present in several high-end car models such as those produced by Mercedes-Benz, Honda, and Audi. The realization of Level 4 highly automated driving and Level 5 fully autonomous driving lies in achieving "autonomy", which is the direction of current autonomous driving research efforts.

Based on large-scale, omnidirectional, and complete traffic information perception, AVs can realize scenario-adaptive driving behavior prediction by comprehensively considering traffic rules, driving experience, etc., using a trained motion planning model to predict the future behavior of surrounding vehicles, to realize autonomous driving.

In recent years, artificial intelligence has developed rapidly, and deep learning and neural networks have been increasingly used in various fields, including transportation. An all-element traffic information perception system can collect a large amount of credible traffic data in a short duration of time, provide rich training datasets for machine learning, and provide accurate and high-quality big data for intelligent driving behavior decisionmaking systems based on learning algorithms. Convolutional neural networks, machine learning, deep reinforcement learning, and other algorithms can be applied to AVs, allowing them to perform intelligent learning, forming a virtuous circle, and eventually achieving intelligent, highly autonomous driving or even fully autonomous driving.

## 3. Virtual simulation experiments

Although an actual vehicle test can provide more realistic results, simulation experiments still offer the advantages of convenience and speed. Considering the authenticity of a training scene, a more realistic traffic problem can be established at the micro level by developing an abstract driving framework that captures the details of human driving, thereby ensuring that various types of complex anthropomorphic driving behaviors are employed in simulation experiments. The controller can be trained using game engines, such as Grand Theft Auto V (GTAV), combined with deep learning, to reduce the collection of actual sample data. After correction and optimization, the controller can be applied to real-world environments to achieve lane-keeping control.

## 4. Prediction of driving behavior in mixed traffic flows

The application of IoV can enable the realization of V2X multiterminal interactive communications. Consequently, behavior prediction between AVs can be more inclined toward using big data, CVI, IoV, deep learning algorithms, etc., to solve prediction problems. However, as manual vehicles still dominate the roads, manual–automatic mixed traffic flow environments will continue to exist for a long time.

In addition, according to current technological development trends and market penetration levels, highly digital and intelligent AVs are difficult to realize in a short period of time. Therefore, research on predictive problems in mixed traffic driving environments with different levels of intelligent connectivity is necessary. Moreover, this is a problem not only for automatic–manual mixed traffic flows, but also between traditional vehicles without intelligence, individual intelligent vehicles, and ICVs of different intelligence levels in an IoV environment. For a new ICV, vehicles can achieve interconnections with other vehicles with the same level of intelligent connectivity. However, for vehicles with other levels, they must be converted to individual intelligent identification and prediction systems. Currently, there is little research on this problem.

# 5. Autonomous "agents"

An autonomous "agent" may be another form of artificial intelligence technology in AVs, but its use is more like putting a mechanical brain into the AV. This means that AVs are not only autonomous but also capable of learning to improve their own understanding of the world.

The driving brain should have the following functions: (1) accomplishing driving tasks independently and safely in various complex environments; (2) continuously learning and updating, performing natural social behaviors and driving behaviors of human beings, which may help in the process of decision-making in an environment where there are multiple autonomous vehicles (or even non-autonomous vehicles); (3) sounding an alarm when security cannot be guaranteed.

However, autonomous "agents" may face enormous legal and ethical issues. On the one hand, the behavior of autonomous "agents" is highly unpredictable. There are concerns about their intelligence level being too low or too high or too. Judgments of accident liability also are cause for concern. After all, it is absurd to convict an AI.

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