Multiple Vehicle Cooperation and Collision Avoidance in Automated Vehicles: Survey and an AI-Enabled Conceptual Framework

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Multiple Vehicle Cooperation and Collision Avoidance in Automated Vehicles: Survey and an AI-Enabled Conceptual Framework

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ABSTRACT

Prospective customers are becoming more concerned about safety and comfort as the automobile industry swings toward Automated Vehicles (AVs). A comprehensive evaluation of recent AVs collision data indicates that modern automated driving systems are prone to rear-end collisions, usually leading to multiple vehicle collisions. Moreover, most investigations into severe traffic conditions are confined to single-vehicle collisions. This work reviewed diverse techniques of existing literature to provide planning procedures for Multiple Vehicle Cooperation and Collision Avoidance (MVCCA) strategies in AVs while also considering their performance and social impact viewpoints. Firstly, we investigate and tabulate the existing MVCCA techniques associated with single-vehicle collision avoidance perspectives. Then, current achievements are extensively evaluated, challenges and flows are identified, and remedies are intelligently formed to exploit a taxonomy. This paper also aims to give readers a AI-enable conceptual framework, a decision-making model with a concrete structure of the training network settings to bridge the gaps between current investigations. These findings are intended to shed insight on the benefits of the greater efficiency of AVs set-up for academics and policymakers. Finally, the open research issues discussed in this article will pave the way for the actual implementation of driver-less automated traffic systems.

keywords: Automated Vehicles, Safety, Comfort, Taxonomy, Conceptual Framework, Multiple Vehicle Collision, Vehicle control.

1 Introduction

Over the last decade, the community of scientists has been paying close attention to research into sustainable technologies, artificial intelligence, and smart city. This trend will continue in the coming years, according to[1]. One area of intensive investigation has been carried out in public transportation service, whereas the automotive industry is heading towards automated vehicles (AVs) intending to boost road safety. Several studies have found that 94% of road accidents occur because of the errors of human drivers[2,3]. Recent AVs collisions during testing, on the other hand, highlight the need for more rigorous risk analysis. The United Nations has targeted a 50% decline in road fatalities by 2020, and we passed the timeline but it remains a dream. Modern scientists want to transfer all driving tasks from humans to machines because the majority of traffic collisions (94%) are caused by human error. It is already proven that replacing 90% of human-driven automobiles on the road with AVs can save 50% of travel time and prevent 74% traffic collisions[4].

Highway traffic incidents cause delays and extra safety concerns in the form of secondary collisions. The term *multiple collision* refers to a collision that involves up to *n* vehicles in the first collision. In altogether, these multiple collisions projected almost 20% of all traffic collisions and 18% of the deaths on United States motorways[5]. Furthermore, multiple collisions were responsible for up to 50% of urban traffic congestion[6]. Because of highway conditions, rear-end crashes accounted for 42.7% of all accidents that usually lead to Multiple Vehicle Collisions (MVCs)[7]. Through an extensive evaluation of recent AVs crash data, we found a crucial indication that the AVs systems are mostly prone to rear-end collisions, the leading cause to happening chain crashes or crashes among multiple vehicles[8]. Additionally, as the transportation community moves from an era of data-scarce to a generation of data-rich, a standard methodological shift from physics-based methods to artificial intelligence techniques is urgently needed to forecast the transportation dynamics of vehicles operating adjacent to human-driven vehicles and help socially optimise policy making[9].

Research on MVCs in AVs highlights the need to follow the evaluation of the consequences of a collision[10]. In contrast, existing research is dedicated to three viewpoints: (1) identifying multiple collisions[11], (2) analyzing multiple collisions' characteristics[12], and (3) multiple collisions' risk modelling[13]. Collision avoidance in high volume vehicle velocity, which leads to MVCs, is considered a high non-linearity vehicle force that demands an optimal motion planning strategy. The current control strategies are validated only at low and medium velocity; a reliable validated strategy is essential for high-speed situations[14]. Regrettably, the continuous AVs research focused solely on collision avoidance strategies for two consecutive vehicles and ignoring the MVCs aspects. The potential researchers create several review articles, and we discuss and compare some of those reviews and journals with our survey focused on the aspects mentioned above. *Table 1* represents the comparison of those aspects.

However, more intensive research is essential for highlighting those principles of examining accidents and preventing chain collisions, which represent the generating mechanism of a traffic accident[15]. In support of this argument, the safety framework of driving action should be built from the viewpoint of the chain collision. The combined potential concerns of MVCs are illustrated by *Figure 1* in four phases: the first phase is the regular driving presentation; the second phase is the pre-crash situation associated with the point of no return; the third phase presents the first crash situation; and finally, the fourth phase is the illustration of MVCs induced by the first collision.

Table 1. Comparison of Autonomous Vehicle Collision (Single & Multiple vehicle) Avoidance Related Survey Papers.

	Survey Coverage									
Ref	SP	CC	TA	DM	VC	DS	CI	SVC	MVC	CS
[16]	✓	✓	✓	✓	✓		✓			
[17]	✓	✓		✓	✓	✓	✓			
[18]	✓	✓	✓	✓	✓	✓	✓			
[19]	✓	✓	✓	✓	✓	✓				
[20]	✓	✓		✓	✓		✓	✓		
[21]	✓	✓	✓	✓	✓		✓			
Ours	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

SP = Sensing & Perception, CC = Communication & Cooperation, TA = Threat Assessment, DM = Decision Making, VC = Vehicle Control, DS = Database & Software, CI = Challenges and Issues, SVCA = Single Vehicle Collision Avoidance, MVCA = Multiple Vehicle Collision Avoidance, CS = Conceptual Solution.

Considering all the difficulties mentioned above, numerous scientists are extensively involved in constructing effective models of AVs for effective collision avoidance strategies.[22] sated the control features of AVs in their survey.[23] investigated the intersections and combining and merging methods of highway on-Ramps.[24] surveyed the control methods of urban traffic signals. Focusing on the distributed control mechanisms depends on the dynamical modelling of AVs[25] made extensive discussions.[26] discussed motion control, focusing on the cooperative longitudinal motion of multiple vehicles.

During a combined approach, different strategies were suggested that focus on improving certain areas or considering all difficulties. As a result, it is necessary to compile all available works in order to gain a thorough understanding of the progress of research in this field. To the best of our knowledge, no similar form of in-depth analysis carried out thus far in the literature. Therefore, a comprehensive taxonomy is demonstrated in this article that differentiates the techniques, methods, and technology offered to date for effective autonomous driving strategies for SVCA (Single Vehicle Collision Avoidance) and MVCA (Multiple Vehicle Collision Avoidance). Subsequently, we review the relevant literature to demonstrate the key ideas of each current study. Essentially, the purpose of this study is to inspire readers to recognize current research breakthroughs in this domain and identify unsolved concerns. Finally, in an AVs system, we offer a conceptual framework of an MVCCA strategy to create an optimal solution.

The followings are the concrete contents of the contributions in this paper:

1. The comprehensive analysis identifies and segments the chain events of collisions associated with MVCs. Both SVCA and MVCA perspectives are reviewed objectively, and a taxonomy consolidates all potential approaches into a single-window for convenience.

2. Recent technologies and protocols are being investigated to determine realistic automated driving decisions and construct the optimal cooperative decision-making method. According to their performance matrix, the practical difficulties and issues are presented in-depth.

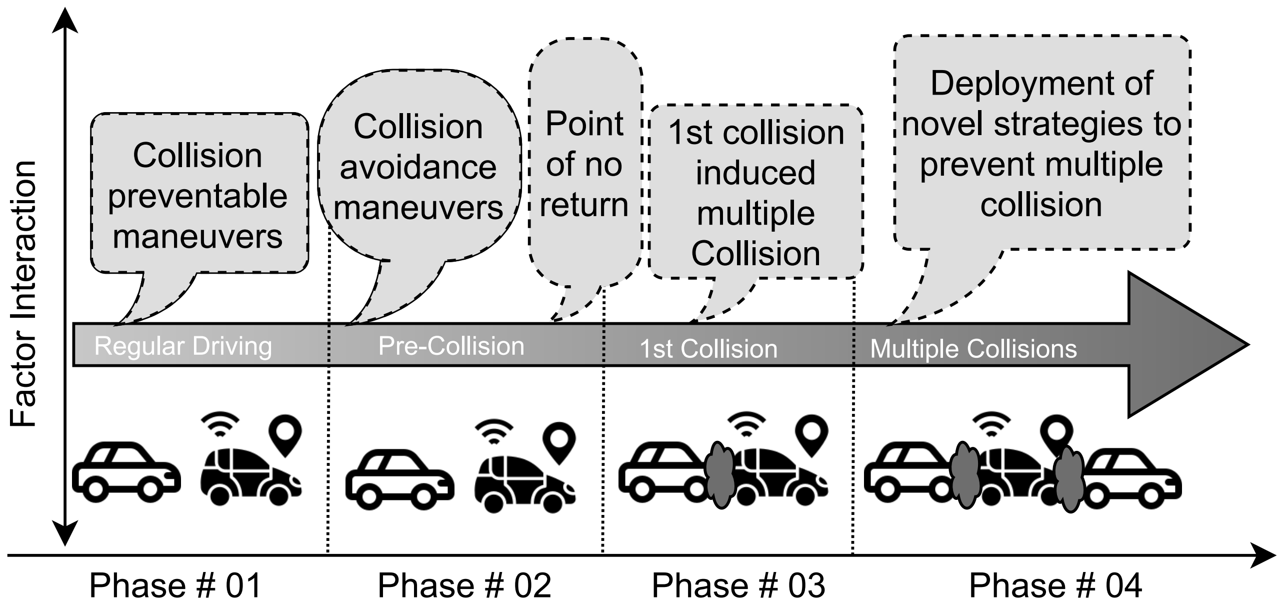


Figure 1. Multiple Vehicle Collisions Illustration in Four Phases.

3. This study offers a future research direction by proposing a AI-enable conceptual framework for MVCCA in AVs. The proposed framework closely scrutinizes five aspects of AVs to guarantee adequate driving strategies. Learning-based monitoring, controlling, and preservation with highlighted applications are also offered in the intended framework to unlock the potential of AVs as standalone MVCCA strategies.

4. An extensive review has shown the existing challenges, including the design issues of optimum decision-making and technical matters regarding essential performance aspects of collision avoidance among multiple vehicles, In this context, we proposed a deep reinforcement learning based decision-making model to control multiple vehicles in multi-agent traffic environment to perform the best action-state map for our automated agents. The proposed model will work to reform the computational aspects of collision avoidance technique optimization according to our proposed framework.

5. Finally, the open research issues are sketched out to allow future research direction on existing works and potential research domain.

As the paper highlights a comprehensive overview of specific topics relevant to the development of the conceptual framework, it enables readers to uncover these topics. The rest of the paper is often adorned with some sections. *Section 2* presents an overview of the AVs and collision segmentation. In *Section 3*, the challenges and issues of avoidance MVCs in AVs are extensively illustrated. The *section 4* represent a Taxonomy of MVCCA and under this taxonomy in *section 5*, a spacious AI-enable conceptual framework deployed for MVCCA in AVs. Priceless future research indications are synchronising in *section6* to give the respected researchers the future challenges. Finally, *section 7* concludes the paper by revealing the article's contribution.

2 Overview of MVCCA

The leading subject in automotive science in recent years has been AVs[27,28]. Millions of lives are likely to be saved soon, considering the remarkable statistics showing that the number of casualties in road accidents has been 1.2 million a year in the last ten years[29]. Furthermore, it will optimize traffic and reduce travel times significantly. Demonstrating the multiple vehicle cooperation and collision sequences, an overflow is presented in *figure 2*. A ray of hope is worth mentioning that the strong gain is self-evident in developing stable AVs. However, their implementation is a major challenge for both the rule-based control and data-driven decision-making science communities. Readers are encouraged to refer to[30,31] for the appropriate analysis of key technologies for assistance systems for collision prevention. Multiple business giants in different countries are currently working on the production of AVs. The *authors* of[32] briefly described the data on the growth of each country in AVs design and the challenges facing by those countries. AVs production in the initial days entails numerous studies and problems. A

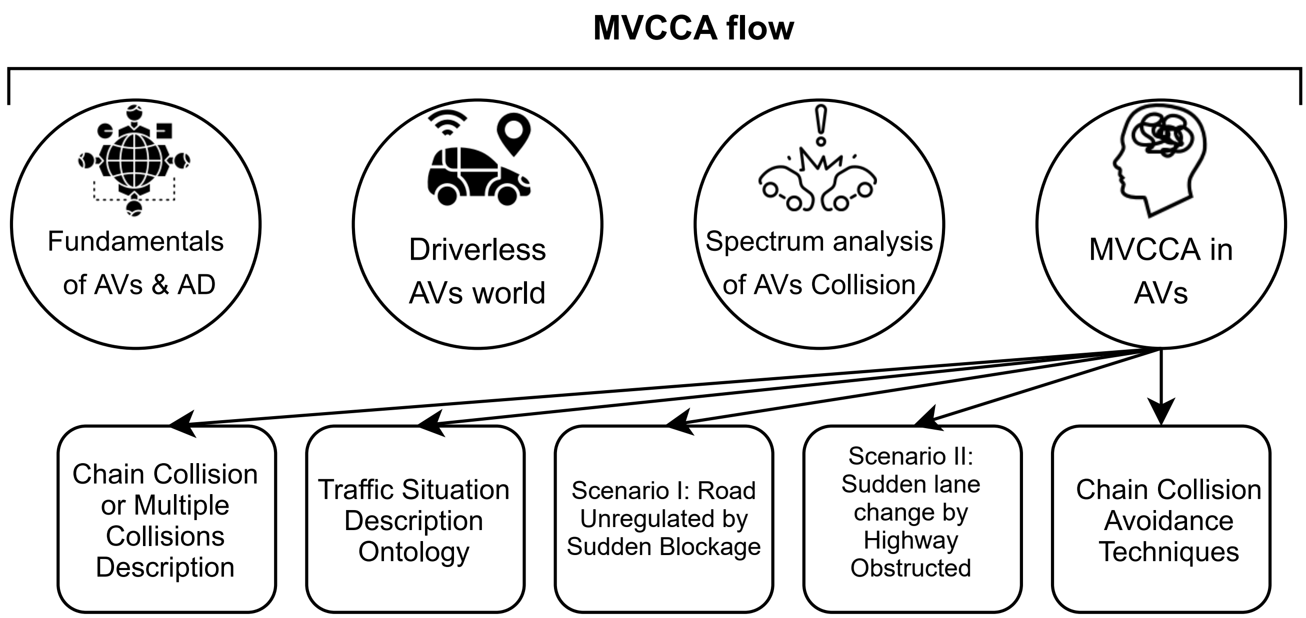


Figure 2. The Overview Flow of MVCCA in AVs.

real-world AVs are never 100% sure what the things, road boundaries, lanes, rules, signals, etc., are in a situation. Instead, it has a level of confidence or degree of certainty about all these aspects[33].

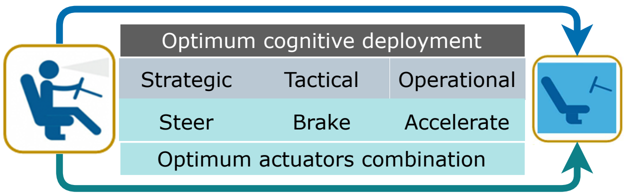
2.1 AVs Fundamentals

In the modern transportation world, autonomous systems have been activated to avoid 94 percent of human driver error road accidents[34]. The AVs are a special kind of device that can sense its surroundings and operate without human interference. *Figure 3a* is the cognitive presentation of AVs basics and the elaborate discussion on automation level of AVs readers could be referred to[35]. The mass production of tools relevant to AVs is approaching thanks to rapid advancements in AVs technologies, particularly the recent advancements in LiDAR, GPUs, and learning control strategies[32]. Many business giants such as Waymo and GM-affiliated automotive and IT firms are working hard to get their advanced self-driving cars onto public roads as soon as possible. The leading peril of optimal performance in AVs technologies is traffic collisions. Thus, the mechanism for accident prevention must be capable of controlling all types of threats during automated navigation, with the progress of the production of AVs. *Figure 3b* depicts the complexity and speed of numerous driving conditions.

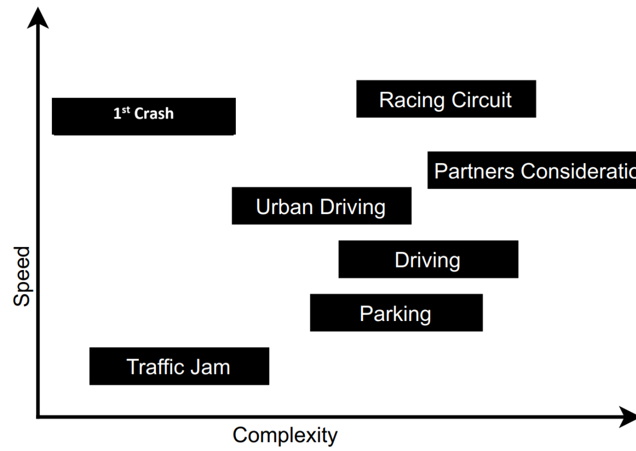
2.2 *n*-number AVs

To date, most of the current research has perhaps concentrated unexpectedly on two polar scenarios, in which either one AV is travelling on a highway in an environment dense with human drivers or an AV network with minimal interaction with human operated participants. The much more realistic but challenging transformation between these two scenarios has received much less attention. But it is this very hybrid human-machinery space, now known as *mixed autonomy*, which merits our collective interest.[36] divided this transformation into 4 stages, the CVs stage: pure conventional vehicles (CVs), the CVs-dominated stage, the AVs dominated stage, and the pure AVs stage. The latter 3 stages are the subject of this article. The difficulty of modelling for each step is shown in *Figure 4*. The CVs dominated and AVs dominated stages, that is, *mixed autonomy*, are very difficult to chart. An understudied process is the unknown and complicated interactions among different vehicle types. The following concepts further split the relative proportion of AVs and CVs into mixed autonomy (indicated in road map in *Figure 4*):

1. *1st stage:* 1 AV + 1 CV (one AV has one CVs interaction).
2. *2nd stage:* n AV + m CVs (Multiple AVs travels a CVs dominated traffic environment).
3. *3rd stage:* m AVs + n CVs (multiple AVs interact with n CVs in the AVs dominated traffic environment).
4. *4th stage:* n AVs (a demand for pure AVs) with replacing all vehicles with AVs. (AVs communicate with each other accordingly).



(a) Cognitive presentation of automated driving basics.



(b) Graphical presentation of driving complexity according to the vehicle velocity.

Figure 3. Evaluations of Driving Complexity in AVs.

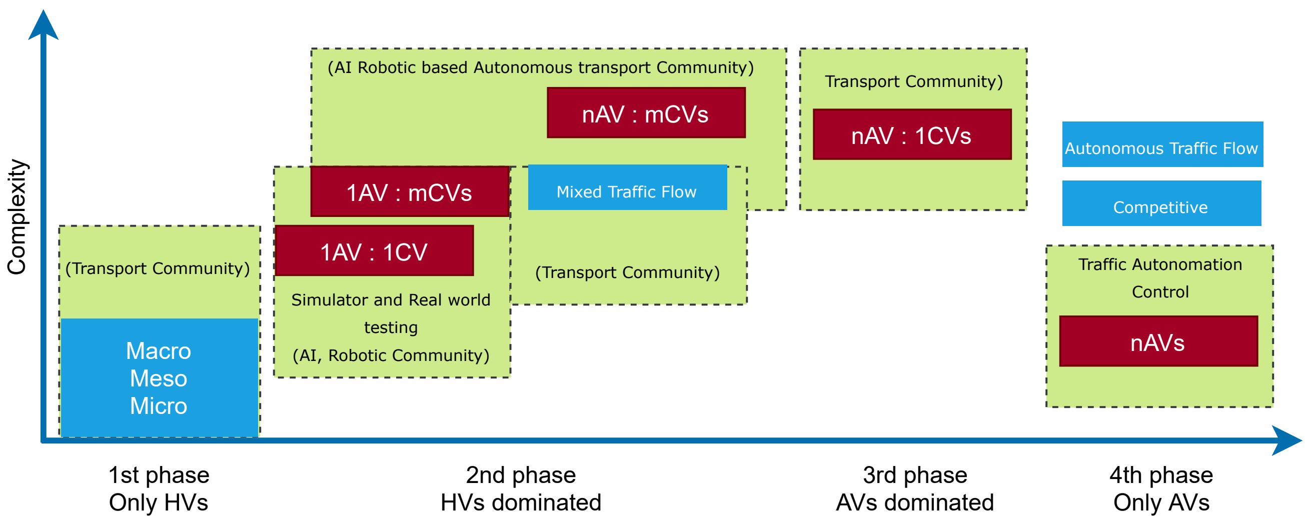


Figure 4. Time with complexity refinement at each phases (according to both researcher and manufacture aspect).

Figure 4, a block-dotted box is included in the group associated with each step. The objective of the transport community is to model first a pure CVs, then a model which is dominated by CVs, and finally pure AVs dominated[36]. However, researchers are more concerned with the step of the CVs dominated operation, in which one or a few AVs navigate the traffic environment.

2.3 Spectrum Analysis of Collision in AVs

Most of the current automated driving research goes far beyond the control of a single vehicle. But in reality, decision-making in crucial scenarios and the initiation of strong sensors, cooperative communications networks, and embedded systems have created extensive concern about how to solve the problem of multiple automated vehicles' cooperative control. The problems of vehicle control by motion planning for a single automated vehicle are usually divided into three segments: 1) the stabilization of points, 2) tracking trajectory, and 3) the path following[37]. For multiple vehicles, formulating a cooperative trajectory generation strategy is the main issue. In particular, a collision-free route is adopted by each vehicle, and all vehicles reach their respective destinations. *Table 2* represents the major aspects of single and multiple vehicle collisions[38].

2.4 MVCCA in AVs

As like the conventional traffic system autonomous traffic traffic system also has potential prospective on both the SVCs and the MVCs. Despite the fact that automakers have focused on creating realistic solutions for AVs to replace human-driven

Table 2. Major Aspects of SVC and MVC.

Features aspects		SVC	MVC
Crash severity		Less severe then MVC	More severe then SVC
Collision types	Static	Very common	Very common
	Dynamic		
	Uncertain		
Cause pattern		Defined situations	Unpredictable situations
Automated approach		Very common	Very common
Avoidance techniques		Study widely	Study marginally
Avoidance algorithms		Study widely	Study marginally
Single and multi agents perception	Agents	Single	Multi agents
	Environment	Less complicated	Very complicated
	Private goal	Focused	Focused
	Common goal	Not focused	Focused
Cooperation driving	Characteristics of cooperation	Location	Agents involved
		Interaction	Location
		Duration	Urgency and costs
		Preparation time	Interaction type
		Initiation	Duration
			Mutuality
			Preparation time
			Initiation
	Examples of cooperative situations	Lane merge	Platooning
		Truck overtaking	Lane merge
			Truck overtaking

vehicles, the most recent solutions are only suitable for single vehicles. On the other hand, road traffic is a dynamic and interactive system. Such a system necessitates a multifaceted approach to solving the issue since it takes into account not only the pedestrians and the surrounding road, but also other road users, which may involve multiple participants[39].[40] investigated and illustrated a region map of single, double, triple, and multiple vehicle collision conditions regarding sudden slowdown.[36] evaluate the steering stability for multiple vehicles in the case of automatic or manual driving, which is restricted for safety. In fact, MVCs are likely to result from a series of unstable coupled groups of vehicles.

2.4.1 Chain Collision or MVCs Description

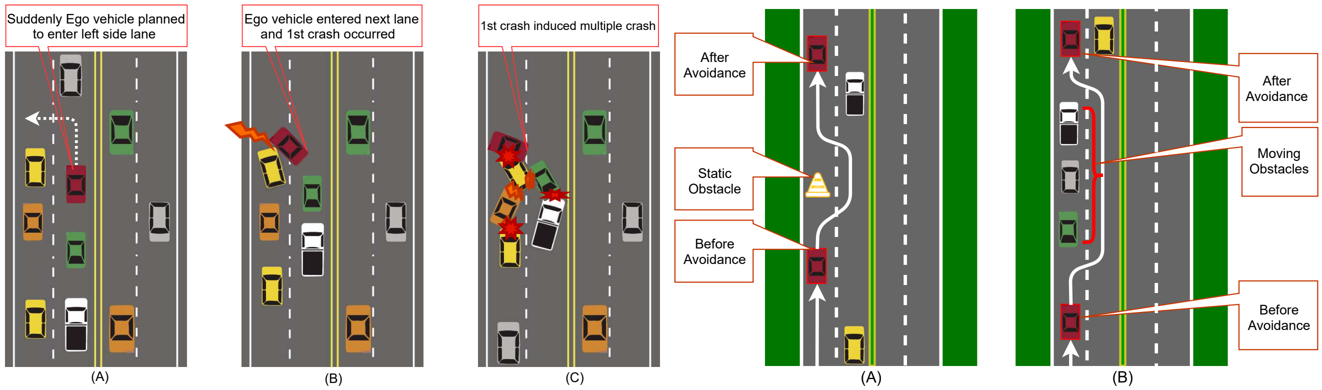
MVCs is the ultimate result of a SVC in traffic system. Drivers on highways frequently rely heavily on the vehicle's tail brake lights to decide if they have the brake[40]. This creates potentially dangerous situations when a vehicle follows another closely, particularly when the ability to see past the vehicle in front of it is limited. The reaction time of the driver between the occurrence and the frequency of the brake is usually 0.75 to 1.5 seconds[39]. This guarantees $70 mph$ before any reaction occurs, and it flies between 75 and $150 ft$[36]. There may be few margins of protection if a short inter-vehicle distance is maintained in order to prevent accidents during abrupt braking. Furthermore, the successive drivers' cumulative reaction times in heavy traffic will lead to a number of secondary accidents and create multiple vehicle accident chains[41].

2.4.2 Traffic Situation Ontology

In a cooperative group of vehicles, the perception process of dangerous situations is discussed in[42]. In the meantime, it has been accepted that a higher degree of situational understanding is often required in order to provide driver assistance. Vehicles have to understand the situation they are involved in. This is or will become the basis for numerous implementations, including advanced crash detection and mitigation systems. The advantage of knowing the scene would allow for automated driving of more than one vehicle to deal with hazardous situations at high speed in complex inner-city environments or cooperative manoeuvres if necessary[43]. Traffic collisions prevent the flow of traffic, block the highway and cause serious congestion. Sometimes, the blockage causes collisions between vehicles. The accident often causes further collisions and leads to a multiple vehicle collision.

2.4.3 Scenario I: Highway Unregulated by Sudden Slow Down or Blockages

We consider a typical highway scenario in which n number of vehicles are traveling in parallel, in front of or behind each other. All vehicles attempt to monitor their own relationship to speed. In this situation, a driver usually relies on the brake light



(a) Multiple vehicle collision scenario cased by sudden lane change. **(b)** Illustration of avoidance technique for MVCs.

Figure 5. Demonstration of MVCs and its Avoidance Technique.

of the car ahead of them to evaluate their own braking action in road emergencies caused by bad weather or misjudgment[44]. In low-visibility situations, the behaviour of the traffic is certainly different from that in natural conditions. With the use of a model of friction-force[45,46], collision among multiple vehicles was investigated in low visibility situations. However, if the emergency incident is caused by multiple vehicles ahead, then it could be too late to stop the collision by the time the vehicle brakes immediately ahead. In addition, the combined reaction time of drivers across all the vehicles ahead will further escalate the situation. Consequently, a single emergency incident may also lead to injuries in multiple chain collisions. Another aspect is that the driver deploys brake matching to the taillights of the leading vehicle and the rearrangement of friction force, which strongly depends on the velocity of the vehicle in the traffic situation. The chain collisions can be caused by the first accident[20,21].

2.4.4 Scenario II: Sudden Lane Change by Highway Obstructed

The first collision caused by sudden lane change can be induced the further collisions and may lead to a MVCs among several vehicles when a vehicle switches lanes on a two-lane highway from its ego lane to the next lane. If a vehicle enters the second lane at a high (low) speed in the ego lane or first lane, it can collide with the next lane or second lane into the forward (rear) vehicle, and the crash can create further collisions[47]. Another scenario is that the three-lane highway is reduced to a single lane due to road work to increase heterogeneity or that the leading vehicle comes to a halt unexpectedly due to a blockage[44]. This roadwork is announced to all vehicles via road signs. According to these signs, vehicles must slow to 70 km/h and then merge into a single lane. As a consequence, the situation becomes more complicated, exposing the differences in the controls. The secondary collisions are typically caused by the first collision and the deep evaluation of this, found in[48]. Potential readers were referred to read[49–51] to uncover secondary collisions. *Figure 5a* is the symbolic consequences representation of the MVCs.

2.4.5 Chain Collision Avoidance Techniques

Reviewing the contemporary research works we usually found numerous solutions and protocols SVC but the MVCs prolems are still sufferd by the lack of concern particularly in the domain of AVs. The traffic situations with multiple vehicles interacting are difficult in AVs system. Even though if another traffic participant's rough intent is understood, all participating vehicles must agree on a cooperative decision which gives a conflict-free trajectory plan, indirectly or explicitly. For each vehicle, the movement must be secure and comfortable and must accommodate all individual goals and desires[52]. The standard interval between these intervals can be determined using the collision free interval for each agent[53]. When each agent's velocity is adjusted in parallel, the velocities in the non-intersecting distance inevitably avoid colliding. This agreement protocol is used to pick competing speeds in a common interval[54]. As a navigation query, collision detection and avoidance in agents[55] or multi-agent[56–58] scenarios has also been addressed.

Theoretically, chain collisions can be avoided or decreased it's severity by reducing the time between an emergency occurrence and the moment when approaching vehicles are told of it. Propagating a vehicle-to-vehicle incident warning alert is one way to do this. This could make it possible to circumvent the usual chain of drivers responding to the activation of vehicle brake lights immediately ahead of them and even allow drivers to react to an incident before seeing it. The secondary collision mitigation strategies discussed in[59,60]. Common strategies are employed for MVCCA strategy as Platooning[61], Active Brake Control[62], Time-Critical Cooperative Control[37], Trajectory Re-planning[63]. *U. Z. A. Hamid et al.*[63] proposed a avoidance technique for chain crash in *Figure 5b*.

3 Challenges & Issues of MVCCA

For combinations of a hundred plus sensors, communications devices, and actuators to navigate it autonomously, extensive evaluations will be needed before mass production of AVs. These matters indicate the analysis of the root causes of AVs failures and finding out the chain events of the potential failures. Obviously, policymakers and researchers are dependent on this kind of comprehensive evaluation to develop the optimum strategies. Several barriers are likely to challenge the advancement and execution of sensible driving technologies, particularly the avoidance of collisions among multiple vehicles. The key factors that could hamper technology adoption before and after its full maturity consist of:

3.1 Mixed Traffic Systems Management

It is proven that technological up gradation is not the outcome of one or two days, but rather the outcomes starting from the 1960s (new models) until now. The same is true for transportation systems. We cannot expect all the road transport systems to convert to automated systems within a day[64]. As a result, it is expected that the transition from the shape of a traditional non-automated vehicle fleet to the shape of an AVs fleet would occur in stages over time. This viewpoint implies that our AVs-based framework would take into account both AVs and CVs (conventional vehicles) at the same time. According to the most recent automated vehicle testing findings submitted by AVs testing companies, the majority of AVs involved accidents are caused by CVs sharing the road with AVs.

3.2 Cooperative Maneuvers for Each Vehicle Safety

Research challenges involve expanding the method to random road geometry and incorporating for each vehicle a plan B trajectory that ensures that in the case of a crash, e.g., loss of contact, a safe state is reached. Although the measurement of cooperative behavioural action[52,65] is almost realistic, with a growing number of participants, it does not scale well. In the AVs traffic system it is more than crucial from the conventional traffic system.

3.3 Multi Agent Robotics Systems

In multi-robot navigation, global path planning and local motion planning play a role in royalty. Autonomous driving is clearly a multi-agent, dynamic field, with the most difficult challenge being to deploy a collision-free, safe, and robust trajectory planning for each of the robots from their starting point to the desired destination.In any unexpected critical situation, the system needs to be capable of re-planning for proper collision avoidance strategy. On the other hand, in multi-agent robot environments, where the agent learns collision avoidance navigation strategies from the environment, it is more challenging to deploy the particular capabilities to find collision-free routes and they are well adapted to all kinds of unseen scenarios[66].

3.4 Adequate Data for Efficient Learning

Machine learning algorithms are currently learning in a supervised method primarily, and therefore, adequate data is needed for efficient learning and a robust training process. Despite the fact that automated vehicles have been tested in highly regulated environments, they often struggle to make the right decisions, sometimes with disastrous consequences. To adapt automated navigation to all forms of critical driving environments, first defining a deriving mechanism in any certain crucial situation would benefit the deployment of a robust driving ability in all the particular scenes. The author mentioned some key critical conditions in[67]. Robust schemes, such as re-planning and retreating the perspective process, would be built to accomplish safe and secure planning in the tackle of uncertainties. Erhan, L. *et al.,* reviewed the anomaly recognition in automated vehicle sensor systems[68]. *Table 3* shows the summery of current available data sets mentioned in Prominent survey papers.

Table 3. Prominent Survey Papers Represented Data-sets with Details Features.

Survey of the Explicate of Environmental Conditions				
Ref.	Data sets	Factors	Critical scenarios	Challenges to handling
69	ApolloSpace, NightOwls	Illuminati- on	Shadow, directly facing the sun, Night	Light intensity variations.
70	AMUSE, CMU, Oxford RobotCar	Weather	Snow, rain, fog	Difficulty in computer vision-based tasks.
71	ApolloSpace, Berkeley DeepDrive	Traffic Conditions	High speed, Multiple collisions, Heavy traffic flows.	Lack of realistic datasets
72	IDD, CCSAD, Highway Workzones	Road conditions	Damage, rough surfaces	Lack of data
Explicate of Behavioral factors				
73	UAH, Argoverse	Vehicle's behaviors	Lane change, overtaking, high speed	Real time prediction in multiple partici- pants
74	JAAD, Daimler pedestrian	Participants and road users' behaviors	Crossing, wrong direction movements.	Lack of datasets

3.5 Simulator & Simulation Studies

Conducting a better automated system generally requires more and more experiments and reshaping of the systems, and it is not always possible to use a real automated vehicle. In addition, performing more deep investigations and configurations that require risky scenarios must be conducted in some type of simulation. Since the 1960s, simulator studies in the automotive domain have been carried out[75].A simulation does not contain any of the actual driving information, meaning that creating a realistic simulation experience both psychologically and physically remains a challenge. Acquisition of sample, simulator fatigue, training of simulator, interface designing, requests for take-over, and the secondary tasks of automated and simulated driving study are examples of these[76]. Traffic simulator in open-source phase as- SUMO[77] MATSim[78] in commercial phase AIMSUN[79] PTV Vissim[80] Paramics[81] VIPS[82], network simulator 802.11p/ITS G5 protocols[83] OMNeT++[84], NS-3[85], Multi-Agent Systems(MAS) LightJason[86]. Potential readers are invited to read the systematic literature review on Agent-Based Simulation of Autonomous Vehicles[87]. The *authors* of[88] evaluated the segmented validity checking systems into A) robustness testing, B) combinatory testing, and C) search based testing methods. In the field of automated driving, there is a need to bridge the gap between open source software and vehicle hardware, see[89] and[86] for ITS simulation systems, respectively.

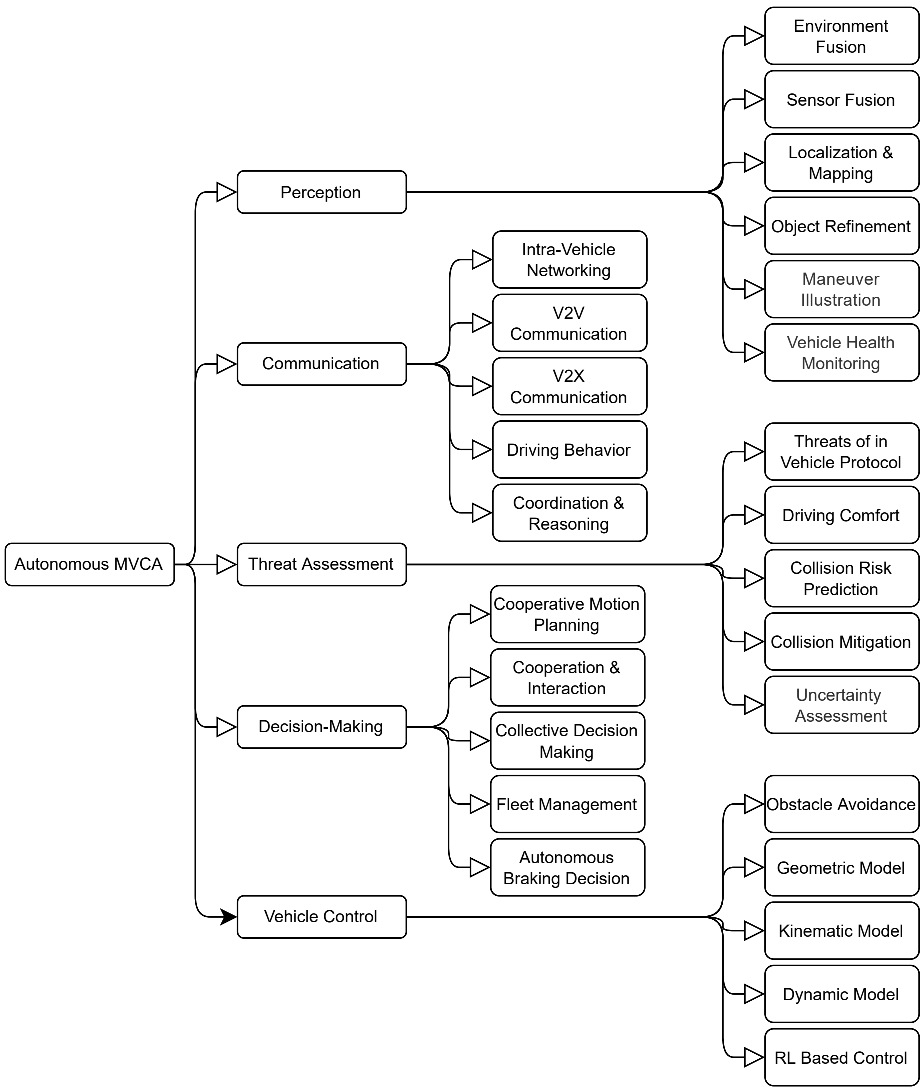


Figure 6. Taxonomy of MVCCA in AVs.

4 Taxonomy of MVCCA in AVs

In AVs systems MVCCA is more complex task than SVCA and in this section, according to the existing research publications we developed an extensive taxonomy. The future of automotive safety is generally predicted to be self-driving and highly AVs, and potential academics and manufacturers are conducting crash avoidance and AVs research to keep drivers and passengers safety. The taxonomy is presented by *Figure 6* to address different perspectives and methods for forming MVCCA strategies associated with the SVCA in AVs.

The basics have been categorized based on the literature's most pressing concerns. To begin, numerous works have been discovered to allow a vehicle to move on its own, with four basic subsystems typically incorporated: location identification and navigation system, environmental situation analysis system, motion planning system, and trajectory control system.The second most prevalent strategy is focused on decision-making model development for vehicle control using physics-based control theories and the latest learning control methods. This section comprises all of the collision avoidance technologies proposed by numerous writers. Thirdly, many studies have been found that aim to provide learning control to prevent single vehicle collisions and adaptive control of single vehicles to optimise the AVs.This segment talks through many forms of perception, communication, threat assessment, decision-making, and vehicle control approaches applicable to a distinct range of technologies. Finally, there are a few studies that offer a complete method of MVCCA strategies utilizing a combination of the five fundamental aspects of the AVs. According to those researches we are going to discuss elaborately in the following sections.

4.1 Perception

The process of perception is entirely dependent on the domain of sense, and its perfectness is a crucial factor in the AVs system's collision avoidance strategies. From the perspective of MVCCA, the fundamental problems are the correct understanding of the road traffic environment, the identification of possible traffic accidents, and the proposal of alternative driving strategies. Contemporary object detection and tracking systems such as 3D object detection for automated traffic systems are offered with a multi-modal 360-degree balancing framework proposed by[90]. Perfect perception process is dependent on several facts which is so crucial for MVCCA and we reviewed some articles to determine the focus feature in the perception phase in AVs and it is shown in *Table 4*. Now the following sections are the some elaborate discussion about these.

4.1.1 Environment Fusion (EF)

AVs have the power to perform automatic actions and navigate themselves based on their surroundings and pre-programmed duties[91]. Based on the environment in which it is operating, AV systems may have varying levels of complexity. Artificial Intelligence (AI) has fueled the improvement and deployment of AVs in the transportation sector. Fueled by large data from numerous sensing devices and improved computer resources, AI has come to be a vital component of AVs for understanding the surrounding environment and creating appropriate choice in motion. For the ultimate objective of self-driving cars, understanding how AI functions in AV systems is essential[91].

4.1.2 Sensor Fusion (SF)

For accurate perception, AVs rely on Sensor Fusion (SF), which requires them to gather input from their surroundings and extract important knowledge in order to classify data by semantic meaning[92] and even anticipate their future states[91]. To do this, the perception approach may utilize a single acquisition procedure or several sensors to constantly scan and monitor the surroundings, much human like vision and other sensations. Collection, filtering, and dealing out of raw data collected from a variety of sensors are all part of the process. In spite of extensive research into on-road driver assistance schemes and autonomous driving systems (including self-driving cars), methods established for the organized traffic of city environment may fail in an off-road setting due to the uncertainty and variety of conditions encountered[93]. The range, signal features, and detection conditions of a single sensor make it difficult to detect obstacles[94]. As a result of this, researchers and technologists are looking into ways to combine multiple sensors and systems. The typical categories of sensors are Image-based sensors, Range-based sensors, and Hybrid sensors, while the most important methods of sensing are Classification-based methods,Probability-based methods, Inference-based methods[95].

4.1.3 Localization and mapping (LM)

For almost 25 years, a continuous localization and mapping system has been a hot topic in the community of mobile robotics. The increasing focus on AVs has accelerated the research attempt with the assistance of automobile manufacturers[94]. The GNSS (Global Navigation Satellite System) could be considered a solution to the problem of location; however, it was immediately demonstrated that this is not sufficient in and of itself[95]. Even though the accuracy constraints of any classical GNSS System are raised when ideally positioned base stations are employed with the Kinematic GNSS, namely Real-Time Kinematic GNSS, availability continues to be a problem in this environment. The use of road infrastructures such as road markings or highway indications to guide a vehicle into a lane is another fundamental approach to localization and navigation[96]. These kinds of approaches, while limiting in their scope as the lateral positioning in the multi-agent traffic environment, are sufficient for contexts where the route can be clearly seen, such as highways. More complicated situations, particularly multiple vehicle traffic environments, may not always give enough road data to locate a car accurately. Moreover, longitudinal position precision is more than crucial in straight, expressway-like situations[97].

4.1.4 Object Refinement (OR)

The quality of a self-driving system's perception task significantly impacts its performance[98]. There has been a rise in the availability of scanners, like LiDAR, which allows for more precise depictions of the vehicle's surroundings, resulting in safer systems. The results demonstrate that contemporary real-time object detection arrangements achieve high performance at the detection rate and the accuracy cost[99]. Hardware and software advancements are expected to lead to a better balance between run-time and detection rate Object Refinement (OR)[99]. However, current real-time OR networks are unsuitable for high accuracy tasks like AVs visual perception[100].

4.1.5 Maneuver Illustration (MI)

The march toward more enhanced driver assistance systems and the advancement of AVs open up new opportunities for the safety system[95]. Improved MI methods may be developed due to increased information accessible in the vehicle regarding the surrounding traffic situations and the path ahead[97]. These systems will utilise this data for control stability during safety-critical manoeuvres. In order to reduce the chance of a collision, such a method might adaptively trade-off between regulating the vehicle's lateral, longitudinal, and rotational dynamics in order to achieve the best balance.

4.1.6 Vehicle Health Monitoring (VHM)

Many factors contribute to traffic fatalities and injuries, including poor vehicle maintenance, unfit drivers, careless driving, a lack of driving instruction, and poor decision-making when it comes to adhering to traffic regulations. Legislative bodies are also to blame for these accidents because they don't have the proper oversight in place. Developing a centralized intelligent Vehicle Health Monitoring System (VHMS) appears to be an excellent answer to this situation[100].

4.1.7 Cooperative Perception (CP)

The precise localization is critical for navigation tasks in related fields such as AVs and intelligent transportation systems. The multi-vehicle perception process and control viewpoints are represented in[101]. Cooperative operations (CO) in multiple vehicle systems are intended to allow participants to trade sensed obstacles or perceived information with one another in order to broaden their sensory horizons, hence increasing their situational awareness and safety[102]. The concept of cooperative and non-cooperative accident avoidance alert methods for overhauling or lane shifting assist and automatic lane shift is represented in another study[103]. Several research areas have looked into cooperative perceptions, incorporating sensor data handling, wireless networks settings, and implementations of unified perceptions[104]. Certain researchers have used sensor fusion solutions to improve the reliability and precision of their data[105, 106].[67] give a flowchart of the cooperative perception procedure in AVs.

Table 4. Perception Aspects of MVCCA in AVs.

Ref.	Features Aspects									Pros	Cons
	EF	SF	LM	OR	MI	VHM	CP	SVCA	MVCA		
91	✓	✓	✓	✓		✓		✓		Presents the methods of sensor fusion.	Not reviewed mixed traffic.
93	✓	✓	✓	✓	✓			✓		Obstacle detection performance.	Multi-agent not in consideration.
107			✓		✓	✓	✓	✓	✓	Discussed on algorithms for perception.	Empowered by DL algorithms only.
94		✓	✓	✓		✓	✓		✓	In off-road environments.	Obstacle avoidance methods.
95		✓		✓	✓			✓		Information-awareness by sensing.	Information used for controller.
96		✓	✓	✓		✓	✓	✓	✓	Discussed on environment perception.	Only simulation platforms.
97	✓		✓	✓	✓	✓	✓	✓	✓	Intention recognition.	Lane illustrated.
98	✓	✓	✓	✓	✓		✓	✓	✓	End-to-end approaches	Only software components.
99	✓		✓	✓	✓	✓	✓	✓	✓	Drawbacks of new automated systems.	Mixed traffic were not checked
100		✓	✓	✓	✓	✓	✓	✓		AI supported applications.	Discussed on sensing systems.

EF = Environment Fusion, SF = Sensor Fusion, LM = Localization and mapping, OR = Object Refinement, MI = Maneuver Illustration, VHM = Vehicle Health Monitoring, CP = Cooperative Perception, SVCA = Single Vehicle Collision Avoidance, MVCA = Multiple Vehicle Collision Avoidance.

4.2 Communication & Cooperation

The second important fact of MVCCA in AVs mentioned in our taxonomy is the Communication & Cooperation (CC). Over the past two decades, advances in robotics, navigation, sensing, computer vision, and high-performance computing have stimulated new automotive innovations, mainly through two streams. Firstly the automation of vehicles, wheres vehicle control functions autonomously without direct driver inputs (such as steering, throttle, and braking). Secondly, the vehicle connectivity consisting of different communication technologies[108] for vehicles, such as V2V, V2I, and V2P[61]. Multiple vehicular communication research[109–113] has been conducted to establish efficient and realistic cooperative communication systems. This work is dedicated to evaluating some existing review and journal papers in this phase by *Table 5*.[112] explored the possible impacts of vehicle communication and mutual awareness using the Vehicular Ad-hoc Network (VANET) Veins simulator.[110] discussed the allocation of vehicle communications services through the use of value-anticipating networks.[114] reviewed communication security in a systematic literature review. The next subsections are some details of CC regarding AVs system.

4.2.1 Intra vehicle networking (IVN)

In the AVs' prospects, the IVN has some viable roles. Improved sensor technologies such as ranging and light detection, cameras, radar, and other sophisticated sensor technologies ushered in a new age in automated driving[115]. A consequence of the inherent constraints of these sensors is that AVs are more likely to make wrong decisions, which can result in fatal outcomes. At this stage, IVN technologies can compensate for sensor shortcomings and are more dependable, practicable, and efficient in boosting information interaction, resulting in improved AVs perception and planning skills and enhanced vehicle control[116]. Inter-vehicle communication is only possible if significant messages that increase safety can be exchanged quickly and efficiently. Many technical issues must be addressed to meet this requirement, involving low latency, high reliability, and guaranteed data rates[117].

4.2.2 V2V Communication

In MVCCA, cooperation and communication are essential. Recent developments in hardware, software, and communication techniques and the creation of diverse functions and standards have enabled the development of new technologies[115]. Vehicle-to-vehicle communication (V2V) technologies are now being integrated into automobiles, which can detect the driving behaviours of other participants. Sensors, communication technologies, and information systems are being unified into vehicles in order to create connected vehicle networks. In interconnected networks, vehicle-to-vehicle communication (V2V) is being applied to decrease traffic congestion, increase passenger safety, and effectively control vehicles on highways[118]. V2V communication generally delivers real-time traffic road state information (e.g., speed, acceleration, position) concerning the ahead vehicles. As part of an active traffic managing method, I2V communication, on the other hand, primarily offers information on downstream traffic circumstances or local speed proposals[119].

4.2.3 V2X Communication

Like V2V Communication, Vehicle-to-everything (V2X) communications have potential in MVCCA. It's also needed for new Internet-of-Things (IoT) applications, including intelligent transportation systems, self-driving cars, collision avoidance systems, and so on[120]. Vehicle IoT faces two major challenges. First, vehicle mobility causes network elements such as communication nodes, accessible wireless sources, and network intensity to shift spatially. Second, the problem is made even more complex because the communication network environment is changing over time. Because vehicle IoT systems incorporate several network nodes and diverse wireless communication techniques, the network situation may change frequently. As a result, we must create a more intelligent communication system that can self-evolve[119].

4.2.4 Driving Behavior

Predicting and planning interactive behaviours in complex traffic situations presents a challenging task[116]. It's difficult to predict and arrange interactive behaviors in complex traffic scenarios. AVs struggle to assess conditions and eventually attain their own driving aims, particularly in situations involving multiple traffic participants who interact closely. It is complicated in a multi-participant setting, and typically, AVs suffer from potential driving policies to avoid single-vehicle incidents and collisions among multiple vehicles[120].

4.2.5 Coordination and Reasoning

The road environment, in general, contains a large number of participants. Cooperative multi-agent systems (MAS) are those in which multiple agents work together to complete tasks or optimize value through interaction[121]. Because of the interactions between the agents, the complexity of a multi-agent problem can rapidly increase with the number of agents or their behavioral sophistication[122]. Mapping, localization, and motion planning are three interconnected competencies that must be present for a robot to operate well. A road or route between two entrenched configurations in a cost field must be calculated while considering mobility constraints, static obstructions, and dynamic obstacles[115].

4.2.6 Cooperative Perception Sharing (CPS)

Recently, in cooperative autonomous driving, the Cooperative Perception Sharing (CPS) concept has garnered increasing attention as a plausible and feasible option to increase autonomous drivings performance (safety, comfort, efficiency)[121]. There are two main types of technical approaches: centralized and distributed. Assuming the first scenario is followed, a single driver is a leader in keeping the other vehicles under control, including coordinating their driving. Each car intends to exchange local information with others, such as cooperative adaptive cruise control (CACC) and cooperative perception-based autonomous driving (CPAD)[123].

4.2.7 Platooning

It is possible to use a vehicle platooning strategy in autonomous vehicles, which involves a lead vehicle and a group of vehicles following it[124]. Cooperative Adaptive Cruise Control (CACC) governs the movement of the cars in a platoon[115]. CACC is an upgrade to Adaptive Cruise Control (ACC) that adds Vehicle-to-Vehicle (V2V) communications and consent to cars to travel in more compact and stable platoons than ACC permits. Most CACC systems necessitate communication between the next vehicle and the car in front of the platoon, depending on which is closer. This can be accomplished through the exchange of data on the vehicles' longitudinal and lateral control systems (e.g., steering) along with management procedures that monitor platoon formation, driving maneuvers, and platoon disengagement[117]. Cooperative Awareness Messages (CAM) are used to exchange this data across the connected vehicles.

Table 5. Communication & Cooperation for MVCCA in AVs.

Ref.	Features Aspects									Pros	Cons
	IN	V2V	V2X	DB	CR	CPS	P	SVCA	MVCA		
115	✓	✓	✓	✓	✓	✓	✓	✓	✓	Discussed network and communication.	Not consider the mixed traffic system.
116				✓	✓	✓	✓	✓	✓	Cooperative actions investigated.	Consider only lane change situation.
117			✓	✓	✓			✓		Technological problems illustration.	Not discussed cooperative aspects
118	✓	✓	✓	✓	✓	✓	✓	✓	✓	Evaluate the crucial challenges.	Not consider mixed traffic.
119		✓		✓	✓	✓	✓	✓	✓	Reviewed existing work.	Only as a form of social-AI capability.
120		✓	✓	✓	✓	✓		✓	✓	Use cases of communication	In-feasibility of current technologies.
121		✓		✓	✓	✓	✓		✓	Present a coordination driving protocol.	With a lane-join situation.
122			✓	✓	✓	✓	✓		✓	Evaluation and framing key facts.	Only some aspect of traffic flows.
123	✓	✓	✓	✓	✓	✓	✓		✓	Multi-vehicle systems.	Discussed a car-following model.
124		✓	✓	✓	✓	✓	✓		✓	Summarization coordination in AVs	Focused on particular conditions.

IN = Intra vehicle networking, V2V = V2V Communication, V2X = V2X Communication, DB = Driving Behavior, CR = Coordination and Reasoning, CPS = Cooperative Perception Sharing, P = Platooning, SVCA = Single Vehicle Collision Avoidance, MVCA = Multiple Vehicle Collision Avoidance.

The coordination of multiple autonomous agents raises several real-world issues. These studies use cooperative multi-agent systems models, whereby agents aim to achieve a common global goal[125].

4.3 Threat Assessment

Threat assessment determines the nature of a situation and assists in the secure operation of intelligent vehicles. Due to MVCCA intended For threat assessment, several critical metrics could be established. It is essential to decide on an appropriate critical metric for resolving certain driving and navigation issues in various driving situations.[126] using an integrated algorithm for predicting obstacles and estimating the state of a self-driving vehicle.[127] claims that the TAS performance will be stimulated by a decision-making scheme that will define the vehicle's next plan of action.

Essential Metric[128] classified them into five groups: kinematics-based metrics, potential field-based metrics, time-based metrics, unexpected driving measures-based metrics, and statistics-based metrics.[129] listed a large set of data with more than 250,000 kilometres of driving data for estimating the frequency of collisions with EVT (Extreme Value Theory). Vision-based road safety identification techniques reviewed by[130].[131] pointed out that automated car systems were first disassembled into vehicle components and transport infrastructure components to identify the risks. Many reviewers reviewed many pieces of literature on the tremendous potential of evolving automotive technology for safety and the environment. The *table 6* refers to threat there, and presents the evaluations of some papers focusing on threat assessment as well as potential features and the upcoming sections are the in depth discussion of some facts mentioned in the proposed taxonomy.

4.3.1 Threats of in-vehicle protocol

Due to the lack of human control, it is critical for AVs to perceive the ambient situations precisely when cruising on the road[127]. AVs require a variety of sensors, including GPS, ultrasonic sensors, light detection and ranging (LiDAR), and millimeter-wave (MMW) radar. Sensors enable AVs to perform tasks such as sensing, obstacle/pedestrian recognition, collision avoidance, navigation, and more. Given the great reliance on sensors, it's possible that if they're blinded, or even intentionally managed, they'll produce lethal disasters[128]. The privacy of in-vehicle network connections, such as the LIN, CAN, or FlexRay, must be taken into consideration[132].

4.3.2 Driving Comfort (DC)

The smoothness and consistency of a path are the two key parameters impacting Driving Comfort (DC) in a multi-agent autonomous driving technique[133]. An uneven road may cause occupant discomfort or even wheel slippage, reducing the vehicle's stability. The smoothness factor is gathered at the present planning phase to minimize chain collisions, but it cannot prevent the construction of a path that is substantially different from a path generated in a prior step[134]. If the difference between the current step's path and the prior step's path is too great, an abrupt transition will occur. Path consistency must be examined to avoid this situation[129].

4.3.3 Collision Risk Prediction (CRP)

Early detection of dangerous conditions and proactive responses aid in maintaining appropriate safety distances. However, because of unexpected, unpredictable situational changes, danger maneuvers and crashworthiness persist an important aspect of vehicle protection, helping to reduce the severity of crashes[127]. The following are criticality measurements for regular automated driving. The Time-to-X-Metrics[128], such as Time-to-Brake[135], Time-to-Collision[129], and Time-to-Steer, are probably the most well-known criticality metrics. Because of their directly relationship to human reaction time, these measurements are frequently utilized in assisted driving. However, they mainly concentrate on collision avoidance using imprecise motion forecasts based on constant velocities and do not take into account unpredictable environmental data. Work on a vehicle cooperative collision avoidance (CCA) approach using the Dedicated Short-Range Communication (DSRC) for the V2V[136]. An unique decentralized and cooperative policy for collision-free motion coordinating of non-holonomic AVs was developed in the study.

4.3.4 Collision Mitigation (CM)

The research direction presented three techniques to single and multiple vehicle collision avoidance, as well as Collision Mitigation (CM): (a) front collision indication; (b) front collision avoidance by decelerating and navigation; and (c) a combination of (a) and (b)[132]. The majority of earlier collision avoidance research did not get an improvement in V2V communication for multiple-vehicle system coordination. The time delay between sensor recognition and driver/agent reaction will accrue and spread upstream in a multi-vehicle scheme. If they follow each other closely, which is common on freeways, this is likely to result in numerous car collisions, especially if the first vehicle does emergency braking[137]. If the ego agent/vehicle is too close to the front agent/vehicle, steering may not be effective. Furthermore, if participant vehicles are in both the lanes left and right, steering could result in a more serious collision (s). A scheme is described as a group of agent vehicles that are longitudinally connected. If the velocity and distance of two neighbouring vehicles in the same lane satisfy certain parameters, they are considered linked. Intuitively, if the leading car brakes, the following vehicle must take prompt action to make sure safety. The time gaps used for realistic road driving are typically $1.4 \sim 2.1s$), although some are as low as $(0.4s$. As a result, most vehicles in the same lane are grouped together in some way[135].

4.3.5 Dynamic and Static Threat Assessment (DSTA)

Though vehicular localization is required for multi-vehicle collision avoidance, several methods presume flawless sensing and positioning and instead use global positioning via an overhead tracking camera to avoid local procedures[137]. However, in order to conduct local collision avoidance accurately in a realistic environment, a vehicle must be able to estimate its own and other agents' and humans' positions without the use of external tools[138]. Furthermore, in a real-world setting, multi-vehicle systems require strategies to deal with uncertainty in their own positions as well as the positions and potential actions of other agents[127].

4.3.6 Uncertainty Assessment (UA)

In complex traffic environment, situation assessment is essential for a good vehicle safety method[135]. An illustration of the contemporary methods ADAS shows that: i) the human-driving procedure involves Observation, Driver Intention, and Driving Action sub-modules; and ii) the ADAS procedure contains Detection and Estimating, Threat-assessment, Decision-making, and Instinct functions[135]. Indeed, ADAS operations are intended to be an idea of just like the human-driving manner, and significant progress has been achieved in broadening the variety and difficulty of situations handled today. Nonetheless, in the presence of several vehicles, a key theoretical difficulty remains how to correctly discern a safe driving behavior from a hazardous one, highlighting the importance of Uncertainty Assessment (UA) in AVs systems[136].

4.3.7 Threat Assessment Strategies (TAS)

As vehicles become more automated, they must be able to analyze risks and evaluate situations in real time. Driver-less vehicles in this scenario should be able to assess risks in a dynamic environment in order to make informed decisions and adjust their driving behavior accordingly[128]. To avoid crashes, we must use a risk estimator that takes into account risk indicators such as (1) the driver's state, (2) the conduct of other vehicles, and (3) the weather circumstances[134]. The Collision Avoidance (CA) system is one of the most important components of ADAS. Threat assessment, path planning, and TAS are commonly included in a suitable CA architecture. Using a combination of these methodologies, there are numerous approaches to construct exact CA architecture[129].

Table 6. Reviewed Up-to-date Papers According SVC and MVC Threat Assessment in AVs.

Ref	Features Aspects									Pros	Cons
Ref	TVP	DC	CRP	CM	DSTA	UA	TAS	SVCA	MVCA		
127	✓	✓		✓		✓	✓	✓	✓	Comprehensive CA system highlighted.	Reviewed an introductory idea.
128	✓	✓	✓	✓		✓	✓	✓		Comparative review of critical metrics.	Considering only three typical scenarios
132		✓	✓	✓	✓		✓	✓		Continuous real-time risk assessment.	Decision made on incomplete data.
137	✓		✓	✓	✓	✓	✓	✓		Human-centered risk assessment.	Not applicable for motion control.
136	✓	✓			✓	✓		✓	✓	Analysis the effect of warning system.	Only in simulation environments.
139	✓	✓	✓		✓		✓	✓		Real-time NL collision prediction.	Interaction-aware model.
135	✓	✓	✓	✓		✓		✓	✓	Identify the harmful situation.	Did not solve the problem.
138		✓		✓	✓	✓	✓	✓	✓	Proposes a proactive cyber-risk model.	Cyber-risk assessment.
140	✓		✓	✓		✓	✓	✓		Analysis of threat-assessment methods.	Cover only single-behavior threat.
141	✓	✓		✓	✓	✓		✓	✓	Survey of existing methods.	Study marginally.

TVP = Threats of in vehicle protocol, DC = Driving comfort, CRP = Collision risk prediction, CM = Collision mitigation, DSTA = Dynamic and Static threat assessment, UA = Uncertainty Assessment, TAS = Threat assessment strategies, SVCA = Single Vehicle Collision Avoidance, MVCA = Multiple Vehicle Collision Avoidance.

4.4 Decision Making

Current autonomous driving system is prone to rear-end collision and its is very typical cause for multiple vehicle collision. An optimum decision-making strategy is need to prevent this types of collision.[142] examine fleet management issues in single and multi-player transportation networks.[143] concentrate in their annual study on recent trends in AVs driving decision-making planning. This review discussed some of the latest findings related to various areas of AVs decision-making and planning in *Table 7*. A valuable review of the decision making and control systems of AV is available at[144].

A rigorous mathematical framework , in[145] formulates and discusses the optimization algorithm for the solution and examines the main details of the implementation of the multi-vehicle motion planning problem.[126] propose a new way of thinking in which agents learn collision as a single agent and then avoid multiple collisions by reversing the trained policy.Major research using quadratic mixed-integer programming (MIQP) has been conducted[146], B-splines[147], polynomials[148],elastic bands[149], and potential fields,[150] in route planning strategies[151]. Contemporary research takes into account the problem of route planning for a single vehicle when multiple vehicles are present in traffic environment. Following subsections are the discussion about the decision-making aspects of multiple participants environment in AVs.

4.4.1 Cooperative Motion Planning (CMP)

CMP (Cooperative Motion Planning) for automated cooperative collision avoidance in a multiple-vehicle setting is a possible future solution to improve traffic safety. This method necessitates a real-time motion analyzer that calculates several cognitive vehicles' cooperative moves. Because path planning is a computationally demanding operation, the planner's computing time must be balanced against the solution's efficiency[142]. Automatic involvement of this support system in dangerous scenarios involving many vehicles may avoid accidents. Because human drivers have a long response time and few opportunities to organize their actions with many other drivers, so they are frequently unable to initiate the right actions[143]. A fundamental requirement for the designed method is planning cooperative moves that avoid or lessen accidents.

4.4.2 Cooperation and Interaction (CI)

Cooperative Multi-agent Systems (MAS) are processes where several agents work together to solve problems or maximise utility by interacting. Because of the interactions between the agents, the complexity of a multi-agent issue can rapidly increase as the number of agents or their behavioural sophistication increases. Because of the difficulty in programming solutions to MAS problems, machine learning approaches to facilitate the search and optimization process are gaining popularity. Typical solutions[152] for dealing with those specific manoeuvres are rule-based methods that use some notion of time-to-collision[144] to ensure that they are only executed if there is more time in the worst-case scenario. Due to the lack of explanation of the situation, these options led to overly cautious behavior. It was suggested that machine learning methods, such as Partially Observable Markov Decision Processes or Deep Learning techniques, be used to infer the intentions of others drivers[153]. However, training machine learning algorithms of this type usually necessitates simulated environments, so behavioral simulation of other drivers is crucial[142].

4.4.3 Collective Decision-Making (CDM)

Various collective decision-making (CDM) procedures have been created in Multi-Agent Systems (MAS) research to obtain consensus over the agents' collected preferences. In automotive applications, voting processes have been used to establish agreements in car-sharing[152], platooning, and leader election in decentralized intersection control[154]. It is able to brake properly, not like the driver's late or poor reply to risky conditions, reducing the vehicle's speed and the severity of the crash. As a result, designing accurate and efficient low-level automated braking control methods or high-level control depending on coordinated techniques is a huge technical issue. Conventional control techniques, like constant time headway (CTH), constant spacing (CS) policy, policy, and sliding mode control (SMC)[142], have a limited ability to adapt to changing driving environments. And cannot make reliable and realistic decisions when CAVs coexist with traditional driver-controlled vehicles[143].

4.4.4 Autonomous Braking Decision (ABD)

To prevent accidents, autonomous braking via accurate vehicle decision-making is crucial, especially in the initial phases of AVs technology[144]. Autonomous Braking Decision (ABD) is completely dependent on the automated braking function (ABF), which is one of the AVs safety core technologies[154]. It can successfully brake, as opposed to the driver's reaction to dangerous situations, which is either too late or inadequate, reducing the vehicle's speed and the accident's repercussions. The intelligent control system, assisted by the present advancement of artificial intelligence (AI), makes decisions based on the present environment and continuously learns and adapts to it[155].

4.4.5 Trajectory Coordination (TC)

One of the concerns in autonomous multi-robot systems is how to avoid crashes between separate robots. Finding a coordinated trajectory from beginning to goal for all robots and then allowing the robots to follow the which was before Trajectory Coordination is one method to this challenge (TC)[156]. 'Classical' prioritized planning, in which robots plan sequentially one after the other, is a frequently used practical method for discovering such coordinated trajectories[155]. This method has been demonstrated to be effective in practice, but it is unfinished, and it has not yet been properly assessed under what conditions the method is certain to succeed. Furthermore, because prioritized planning is a centralized algorithm, it is unsuited for decentralized multi-robot systems and the avoidance of chain collisions[157].

4.4.6 Longitudinal and Lateral Constrains (LLC)

In collision avoidance decision-making, optimisation methods simultaneously defeat decentralization effects[145]. They use Longitudinal and Lateral Constraints (LLC) to optimize a cost function concerning a collection of states and the input[158]. Because several motion planning issues are non-convex, optimization problems may become stuck in local minima and become computationally inefficient. Optimization issues can become stuck in the local bare minimum and inefficient to solve because many motion planning problems are non-convex. Deploying the optimal collision avoidance decision-making approach in both single and multiple vehicle collisions is a system need[156].

Table 7. Various Areas of Autonomous Vehicle Decision-Making and Planning Focused on MVCCA in AVs.

Ref	Features Aspects									Pros	Cons
Ref	CMP	CI	CDM	FM	ABD	TC	LLC	SVCA	MVCA		
142	✓	✓	✓	✓		✓	✓	✓	✓	Framework for multiple players.	A computational technique.
143	✓	✓	✓	✓		✓	✓		✓	Behavior-aware planning.	Consider particular cases.
152		✓	✓		✓	✓	✓		✓	A Generic Mixed-Integer Formulation.	Not considering multi-agent case.
153	✓		✓		✓	✓	✓		✓	Cooperative conflict resolution.	Computational complexity high.
154		✓			✓	✓	✓	✓	✓	Cooperative trajectory planning for MV.	Arbitrary road geometry.
145		✓	✓	✓		✓	✓		✓	Motion planning for multiple vehicles.	Exclusively by preplanning step.
157	✓		✓		✓	✓	✓		✓	Tracking and decision making.	Especially stochastic policy.
155	✓	✓		✓	✓	✓	✓	✓		Review on motion planning.	Highway geometric planning.
158	✓	✓		✓	✓	✓		✓	✓	Decision-making in multi-agent.	Lead extreme time consumption.
156	✓	✓		✓	✓	✓		✓	✓	Decision-making highly automated Vs.	May need more research.

CMP = Cooperative Motion planning, CI = Cooperation and Interaction, CDM = Collective decision making, FM = Fleet Management, ABD = Autonomous braking decision, TC = Trajectory Coordination LLC = Longitudinal and lateral constrains, SVCA = Single Vehicle Collision Avoidance, MVCCA = Multiple Vehicle Cooperation and Collision Avoidance.

4.5 Vehicle Control for MVCCA in AVs

According to the proposed taxonomy, Motion planning, decision-making, and vehicle control are critical for multi-agents to navigate their environment. In this section, we review a set of the most relevant review articles and journals in the prospective of both single and multiple automated vehicles. We evaluate the main features as well as their discussion limitations in additional review papers in *Table 8*. In the coming subsections we discussed some details of every aspects of our taxonomy.

In order to take into account the prevention of collisions and the mitigation of impacts in a multi-vehicle collision situation, it is only appropriate to take into account a longitudinally coupled structure evolving of nearly followed vehicles. Coupled refers to two adjacent agents in the same lane if such criteria are met jointly by their speed and distance[159].[156] examined the existing controller system in a mixed traffic system and concluded that the human driver car should be accurately modelled as an essential agent in shared drivers' vehicle control systems in terms of cognitive processes, control mechanisms, and decision-making processes. Considering multiple agents' traffic patterns,[160] reviewed and presented an architecture for Integrated Vehicle Dynamics Control for a quicker and more versatile design to help car manufacturers and suppliers.

4.5.1 Obstacle Avoidance (OA)

The most difficult task in autonomous driving systems is avoiding both static and moving obstacles, which is still hampered by optimal policy procedures[161]. The problems arise from an integrated process of detecting and interpreting the surroundings and impediments, as well as the production of appropriate behaviours[162]. As a result, having a superior control strategy that can drive in an urban setting without colliding with other vehicles and objects is desirable[163]. The majority of current research does not concentrate on the sub-task of obstacle avoidance (OA) in specific driving scenarios. However, on the normal road, other vehicles or obstructions can have a significant impact on the car, therefore OA is a problem that AVs must overcome. Cars can collect data and route information, such as road conditions and location estimations of static and dynamic objects, and use it to forecast actions taken by other vehicles and infrastructure in real time[164].

4.5.2 Geometric Model (GM)

The recognition of moving objects is frequently required in the first step of computer vision applications based on movies[161]. After that, background subtraction is used to segregate the foreground from the background. However, the main objective is to use the background removal techniques in research in real-world applications such as traffic surveillance[165]. However, a review of the literature reveals that there is frequently a detachment between current approaches utilized in real-world applications and current techniques in basic research. Furthermore, the videos assessed in substantial-level datasets are not comprehensive, as they only reflect a portion of the full range of issues encountered in real-world applications[166]. For example, for image data synthesis, a visual structure is applied to produce an estimated geometric representation of an object, whether the image input is static. The second example enables the creation of an image-based human model that may be utilised for optical motion capture[167].

4.5.3 Kinematic Model (KM)

To detect unanticipated variations in participant and ego behaviour, a kinematic framework based on physical phenomena of kinematics is used[160]. The kinematic model is also used to detect unexpected deviations by leveraging information from the leader vehicle, which is directly conveyed and monitored by the leader's nearby cars and supporting infrastructure. The KM is reliable, but not optimal, in particular in the MVCCA aspect[162].

4.5.4 Dynamic Model (DM)

The majority of technical obstacles arise from the unpredictable environment in which AVs operate, such as road and weather conditions, perceptual and sensory input data mistakes, and ambiguity in pedestrian and agent vehicle behaviour[26]. A robust AV control algorithm should account for many sources of uncertainty and generate measurable safe control rules. Furthermore, algorithms that follow precise security measures can aid legislators in handling AV-related legislation difficulties, such as insurance policies, and ultimately persuade the public to accept AVs on a large scale[164].

4.5.5 RL based control

The reinforcement learning (RL)-based automated decision-making strategies function relatively well enough in autonomous driving systems because of this ongoing learning and feedback feature. Researchers have fantastic solutions for enhanced autonomous decision-making and control for AVs.[167] propose a deep Q-network-based automatic braking system to avoid vehicle-pedestrian collisions (DQN).[165] Create a cooperative adaptive cruise control (CACC) automobile controller based on RL. Recently,[167] proposed a framework for CACC systems based on supervised reinforcement learning (SRL).[168] overcome the coordination problem in autonomous driving using multi-agent reinforcement learning (MARL).

4.5.6 Cooperative Control (CC)

The majority of studies on multi-AV control fall under cooperative coordination[160]. In other words, AVs are expected to connect for global traffic information and optimize a common goal of improving traffic flow. In multi-robotic applications, cooperative control has received a lot of attention[169]. For a group of robots with a centralised aim to achieve a task collectively, swarm intelligence, formation control, and consensus control have all been widely employed, as has multi-AV control[164]. A centralized controller or planner coordinates the movement of vehicles in a cooperative multiple vehicle systems to achieve a shared goal, like collectively stabilizing traffic flow and smoothing traffic jams, optimizing driving comfort, or improving fuel efficiency[167].

4.5.7 Non-cooperative Control (Non-CC)

A multi-agent system is a collection of vehicles that interact in a shared environment that they detect with sensors and act on with actuators[164,167]. Distributed control, Robotic teams, resource management, data mining, collaborative decision support systems, and other disciplines use multi-agent systems[167, 168]. They may emerge as the most natural way of looking at a system or provide an alternative viewpoint on systems previously thought to be centralized. Robotics, telecommunications, distributed control, and economics are just a few fields where multi-agent networks are finding use. Due to their complexity, many tasks that arise in these fields are challenging to solve using pre-programmed agent actions. However, the agents must use learning to find a solution independently. A substantial portion of multi-agent learning research focuses on reinforcement learning techniques[167].

Table 8. According to Latest Works the Major Features of Vehicle Control for MVCCA in AVs.

Ref.	Features Aspects									Pros	Cons
	OA	GM	KM	MD	RLBC	CC	NC	SVCA	MVCA		
161	✓	✓	✓	✓		✓	✓	✓		A nonlinear vehicle models.	Focused only modeling.
169	✓	✓			✓	✓		✓		Vehicle control DL methods.	Deep learning methods only.
160		✓	✓	✓			✓	✓		Reviewed control techniques.	Path tracking concepts.
26	✓	✓	✓	✓		✓		✓		Trajectory motion controller.	Verified only in simulation (Carsim).
165	✓					✓			✓	Cooperative navigation algorithm.	Not guaranteed to deadlock avoidance.
162	✓	✓		✓			✓	✓	✓	Cooperative approach for multi-agent.	Strategies verified only in simulation.
163	✓	✓		✓			✓	✓		Investigate the trajectory modeling.	Multiple vehicles not in consideration.
167	✓	✓		✓		✓		✓	✓	Computational techniques.	Inter modal fleet planning.
164	✓	✓		✓	✓	✓		✓		Test and compare decision and control.	Simulate interactive driver behavior.
168	✓				✓	✓			✓	Vision-based DL and RL methods.	The perception input was static.

OA = Obstacle avoidance, GM = Geometric model, KM = Kinematic model, DM = Dynamic model, RLBC = RL based control, CC = Cooperative Control, NC = Non-cooperative Control, SVCA = Single Vehicle Collision Avoidance, MVCA = Multiple Vehicle Collision Avoidance.

5 Conceptual Framework of MVCCA

5.1 Proposed Framework

According to the existing research works we have been developed our taxonomy to solve the MVCC problem. Moreover, illustration of current automated vehicles (AVs) research work has shown that multiple factors and indicators causing vehicle crashes are not thoroughly defined, categorized, or modelled in an embracing context that can be incorporated into applications. Research on multiple agents in AVs is more complex and undiscovered until now. We elaborately reviewed contemporary research and then created a novel approach to collision avoidance strategies in AVs. Now regarding to the MVCCA we proposed an IT-enable conceptual framework that has five phases. Due to focusing on the decision-making phase, we also proposed a reinforcement learning based model to make a perfect driving decision for avoiding chain collisions or mitigate the chain collision severity. We need to train our model by trial and error to adopt our kinematic constraints[170]. The *Figure 7* shows the proposed conceptual framework for MVCCA in AVs, and following sections we will discussed briefly about all the five phases.

5.1.1 Perception Phase

From the review works in *section 4* we got that, due to the mitigation of multiple vehicle collisions, the perception of a multiple agent environment can obviously be more sophisticated than regular driving. Utilizing the segmentation and detection algorithms, we divided the risk prediction phase into two distinct stage where our risk index for multiple vehicle collisions is normally zero when only one road user is detected. It will become high when it detects two or n number of partners surrounding itself. The risk index will reach a high level when the first crash occurs for any unpredictable reason, in this critical situation, we suggests the vision-based supervised learning perception methods that are now very popular in the AI community. In the proposed framework, making a local processing scheme could be suggested to achieve highly accurate localization. Map-supported localization algorithms use to conduct the local features. In particular, we defined the simulations by considering the prominant method as simultaneous localisation and mapping (SLAM). The aim of framing SLAMi is as a Bayesian filtering problem is to estimate the joint posterior probability,

$$P(x_1 : k, b|s_1 : k, q_1 : k-1) \tag{1}$$

b is the map and $x_1 : k = x_1, \ldots x_k$ the robot trajectory given its sensor measurement $s_1 : t = s_1, \ldots s_t$ and the device inputs $q_1 : k-1 = q_1, \ldots q_(k-1)$. In this group, Kalman filter is common methods. The RBPF shows a particle the trajectory of the vehicle and the corresponding map and factories, the probabilities as follows:

$$P(x_1 : k, b\,|s_1 : k, q_1 : k-1) = P(b\,|x_1 : k, s_1 : k).P(x_1 : k|s_1 : k, q_1 : k-1) \tag{2}$$

Here, the posterior probability is calculated by a particles filter. $P(x_1 : k,\, b|s_1 : k, q_1 : k-1)$ in which the previous distribution is derived from the odometry of participant vehicles and refined with sensor interpretations in a multi-agent dynamic environment.

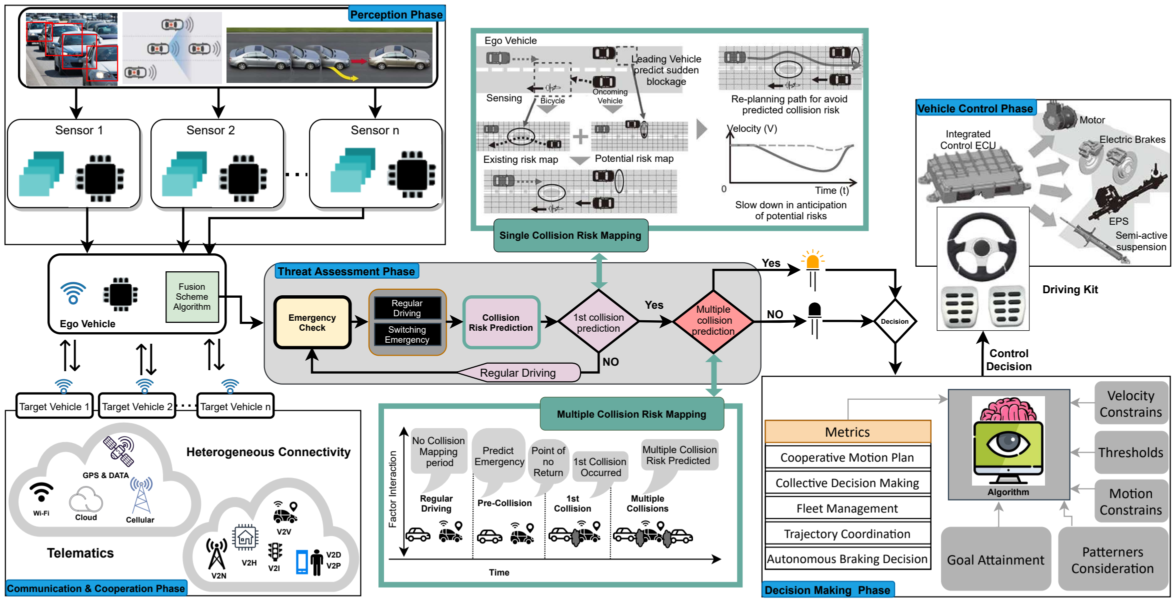


Figure 7. Proposed AI-enable Conceptual Framework for MVCCA in AVs.

5.1.2 Communication and Coordination Phase

This is the second phase of our conceptual framework for MVCCA in AVs. In the multiple agent traffic environment, platooning, lane merging, and truck overtaking are the extreme cooperative coordination situations with patterns of road users. Some critical conditions as after the occurrence of the 1st crash, despite the high risk of 2nd, 3rd or multiple crash, there are situations that are not clearly or unproductively controlled and where cooperation is required to avoid the chain collisions. Therefore, as far the communication medium is a concern, two high standards would be set with 5G, a promising choice for the system. If a unified level of preparation is preferred, C-V2X has to be chosen for backend communication. IEEE802.11p is also would be sufficient for decentralized planning with coordination. A combination of both methods is, of course possible again, whereby routing information is obtained from a central planning level via c-V2X, but manoeuvre planning could be organized via V2X locally.

5.1.3 Threat Assessment Phase

In our proposed conceptual threat assessment phase will estimate the situation's criticality and aids in ensuring safety in the automated traffic system. Two critical metrics have been suggested (See the *figre 7*) for threat assessment namely single collision and multiple collision, and the selection process of the critical metric must be good for specific driving actions in diverse driving environments. The previous *section 3*) provides a comparison of vital indicators with an emphasis on real-time automated driving strategies. According to that comparison, we would like to suggest the reinforcement learning based techniques that are required by automated systems operating in complex, dynamic, and interactive environments that generalize the interactions with multiple traffic participants to unforeseen circumstances and timely rationales. We presented a in-depth framework in our previous work in[171], where we utilized the critical condition prediction technique depending on recurrent neural network based technique.

5.1.4 Decision Making and vehicle Control Phase

In our proposed conceptual framework, the last two phases namely Decision Making and vehicle Control are the top most concentrated phases. From the previous sections we can say that the AVs decision-making process must deal with a diverse set of situations, communicate with other traffic participants, and should able to take into account a set of sensors information from the environment as well as the uncertainty. It is impossible to manually predict all circumstances that may arise and code a suitable behavior. Therefore, considering methods focused on machine learning to train a decision-making agent is convincing. A desired feature of such an agent is that it does not only deliver a recommended decision, but also measure the uncertainty of the decision in question. Deep neural networks (DNNs) are a common artificial intelligence technique for learning after large quantities of data with little human input or without any human interactions (i.e., RL methods). The developed agents that are learned and can operate in unpredictable, broad and stochastic contexts, as revised. The agent has been particularly trained by the effective way of a combination of Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL)[172]. We proposed a multi-agent DRL based an ideal driving strategy for avoidance or mitigating multiple collisions. Followings are the details of the proposed MVCCA strategies decision making and vehicle control mechanism.

RL Method: A reinforcement learning (RL) method may learn how an agent should behave in order to maximise the predicted cumulative rewards by interacting with the environment for a specific activation in a specific state. Existing RL algorithms are categorised into two key types: value-based and policy-based methods. Value-based RL methods, which use neural networks to solve value functions. The main advantage of policy-based RL methods is in the phase of optimization, which can directly improve policy optimization while continuing stable over time during approximation. Regarding our objectives which we defined in previous sections, here, we proposed a policy-based RL approach to address multiple collision avoidance issues. The general form of loss function for RL policy updating, in a stochastic RL where $\hat{\mathbb{E}}_t$ is the expectation policy π_θ, and at time step t, $\hat{B}_t$ is an estimator of the function and the mathematical expression is,

$$\mathscr{L}(\theta) = \hat{\mathbb{E}}_t \left[\log \pi_\theta(\alpha_t|s_t)\hat{B}_t\right] \tag{3}$$

Although performing several optimization steps on this, $\mathscr{L}(\theta)$ (loss function) can seem appealing and straightforward, all the factors may pose problems, such as the prevalence of sample inefficiency, the exploration and exploitation trade-off, and the learned policy carriages unwanted high variance. In practice, this frequently leads to major policy updates, and it will be harmful at a future time step of a training episode because it can change the distribution of observation and reward. In contrast, it is important to use an actor-critical mechanism for modifying a policy that can combine the advantages of conventional value-based and policy-based approaches in the loss function $\mathscr{L}(\theta)$), some developed policy based algorithms such as PPO and TRSO. For simpler implementation, PPO is more convenient than others because of its less computational cost. PPO offers paired substitute loss function, a feature that can be combined as a policy substitute and an error term of value-function, and can be express as follows:

$$\mathscr{L}_t^{goal+UF+P}(\theta) = \hat{\mathbb{E}}_t[\mathscr{L}_t^{goal}(\theta) \; - \; K_1\mathscr{L}_t^{UF}(\theta) + K_2P(\pi_\theta|(p_t))] \tag{4}$$

Here the paired substitute goal is $\mathscr{L}_t^{goal}(\theta)$, K_1, K_2 are coefficients, $\mathscr{L}_t^{UF}$ is the value function's squared error loss $(U_\theta(p_t) - U_t^{targ})2$, and the loss of entropy denoted by P. Specifically, the paired substitute goal is $\mathscr{L}_t^{goal}(\theta)$ takes the form as,

$$\mathscr{L}_t^{goal}(\theta) = \hat{\mathbb{E}}_t\left[min(r_t(\theta)\hat{B}_t, goal(r_t(\theta)), 1-\varepsilon, 1+\varepsilon)\hat{B}_t\right] \tag{5}$$

Here, ε is hyperparameter, $r_t(\theta)$ is probability ratio of $r_t(\theta) = \pi_\theta(\alpha_t|s_t)/\pi_{\theta_{old}}(\alpha_t|s_t)$. The probability ratio r is goal objective whose paring is at $1-\varepsilon$ or $1+\varepsilon$, and it depends on whether it is a positive advantage or a negative advantage, forming the paired goal target as well as the ultimate goal after multiplying $\hat{B}_t$, is the approximate advantage. In contrast to unpaired version, also known as the conservative policy iteration algorithm's loss function, the ultimate value of $\mathscr{L}_t^{goal}(\theta)$ takes the minimized value of this paired goal objective and unpaired goal objective $r_t(\theta)$, essentially avoiding a broad policy update.

The PPO algorithm typically utilises a stable length-N trajectory segment that runs the N-time steps of policy in each iteration, and each M parallel actor collects data at each time step. It uses a simplified version of the generalised gain estimate, which looks like this:

$$\hat{B}_t = \delta_t + (\gamma\lambda)\delta_{t+1} + \ldots\ldots + (\gamma\lambda)^{N-t+1}(\delta_{N-1}) \tag{6}$$

the discount factor here is γ and γ *and* $\delta_t = r_t + \gamma V(s_{t+1} - V(s_t)$. Then the loss $\mathscr{L}(\theta)$) is created by *PPO* and *SGD* is the optimizer with mini-batch , for epochs K on these time steps MN of data.

5.2 Proposed Control Learning Model

The decision-making model for vehicle control in the multiple agent traffic environment is defined as a Hierarchical DRL method depends on three DRL techniques where the maximum Q value will be taken for deploying the best driving policy or set of actions. By comparing the sets of actions, value functions according to the recent states of their respective functions, compound functions optimise the DRL control actions outcomes. When all Q values are compared from 3 DRL schemes, high-preforming value function targets and create a new set of value function from all learning control functions. The choice of a high value would boost the value of goals with a preference comparison that improves the control goal option during selection. The algorithm flowchart of our proposed decision-making for vehicle control is presented by the *Figure 8*.

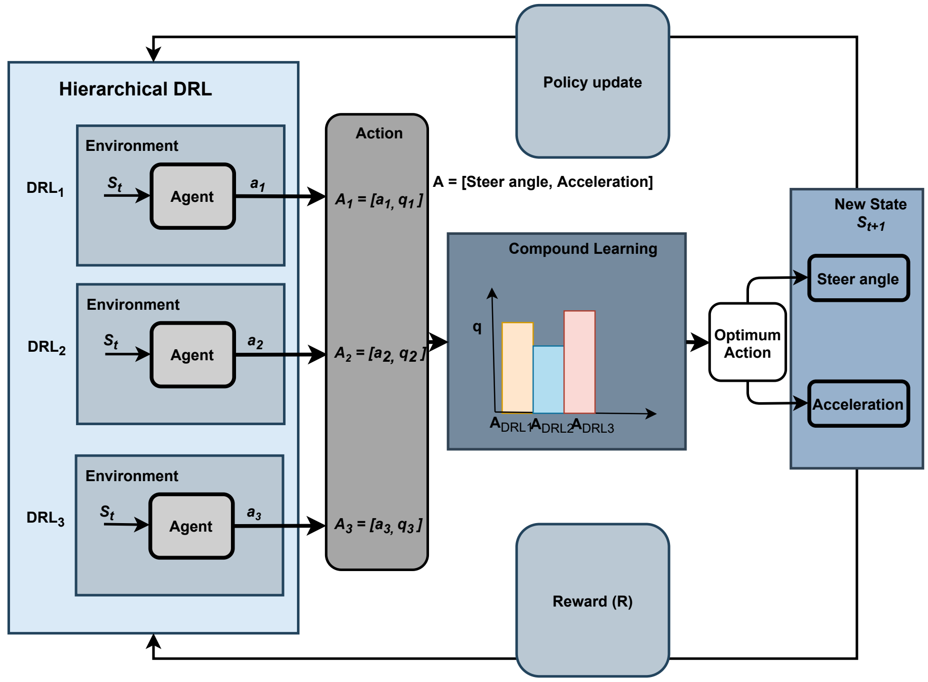


Figure 8. Proposed Decision-Making Model for Avoid MVCs

5.3 Proposed Network Settings

According to the proposed AI-enable conceptual framework presented in the *Figure 7* for MVCCA now we defining the prospective network settings of the suggested training model. For the decision-making and vehicle control processes, this network architecture has two basic elements: a neural network settings and a simulation environment. In particular, dealing with the neighbouring partners in order to achieve a high-level policy for decision-making to MVCCA, three RL algorithms would be use the compare the training performance. The suggested simulator will Unity3D Game Enginei and a multi-agent traingng environment will be create to collaborate with a partner training agent in a high-fidelity traffic environment suite to deploy the simulation. The multiple vehicles in the context of multi-agent traffic environment that includes various road networks and various traffic tasks setups will be execute. *Figure 9* represents the learning model of the proposed training phase of the system. In the training period, the ego vehicle first obtains feedback from the environment by way of our control rewards for the safety, smooth, and efficient driving actions of the ego vehicle and the state of its surrounding partner vehicles, and these countries are transmitted through the network. Next, the self-wheel determined the actions of longitudinal and lateral based on a defined policy network and subsequently returned the action to the simulation environment to model the movement and measure the corresponding reward in the next step. The award function integrates key objectives of the proposed architecture, which are to develop a safe, efficient, and comfort-based automated collision avoidance strategy. In order to achieve the best results, the following factors must be prioritized:1) to comfort: assessment of jerk (depends on its lateral and longitudinal movement), 2) to efficiency: estimation of total time and distance between participants, and 3) to safety: assessment of collision and near-collision risk.

6 Open Research Issues

In the realm of automated driving, we have identified several critical areas for open challenges. We believe that artificial intelligence will play a key role in overcoming these challenges:

1. The proposed framework states that the combination of diverse sensor data becomes essential for a promising sensing system. It is worth mentioning that important advances in object recognition and detection have been reported[173]. However, the existing systems are intended to calculate 2D or 3D bounding boxes for a few trained object classes. As a result, it is expected that future research will focus on bridging the gap between 2D image data and LiDAR-based 3D data, as well as enhancing identified details to allow more objects to be perceived and tracked in real-time.

2. Real-time needs must be addressed to process massive amounts of data acquired from the vehicle's sensors and update AI method parameters across higher speed communication connections[174]. The progress in semiconductor chips for

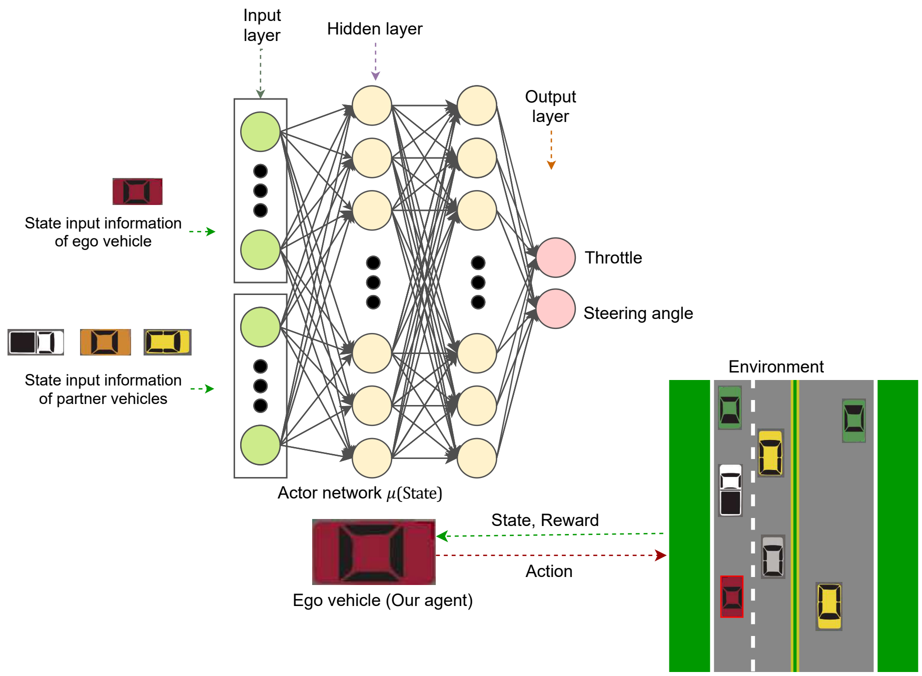


Figure 9. Proposed Network Settings of the Training Process

self-driving vehicles and the growth of 5G networks can overcome these limitations.

3. The collision risk evaluation system must fundamentally forecast the vehicle's gesture throughout a time horizon too short to medium[175]. As noted by various sources, the key focus of deep learning for AVs is perception and the learning process[176]. However, AI is projected to play a considerable role in local trajectory assessment and planning in the coming years.

4. Since the traffic environment is changing, a vehicle might potentially exceed ordinary road restrictions in an emergency or on an expressway. It is therefore vital to thoroughly investigate how to evaluate the content of this uncertain situation. After all, the multi-modalities (mixed traffic systems) and multiple actors dealing with diverse sub-problems, as described previously in section 2, are extremely challenging, and the optimal solution has yet to be revealed. This paper shows that strategic, tactical, and operational collision prevention problems have deeply interacted and should be handled in an integrated way.

5. It is challenging to incorporate non-linear vehicle dynamics in real-time in high-speed collision situations. More complex circumstances can also be employed for the future performance of collision avoidance systems, like avoiding unexpected slowdowns and abrupt lane changes. The collision evasion system protects the provision of a broad collision scenario that shows the best research problem for the future.

6. Typically, the trained conventional machine learning model cannot capture all critical traffic scenarios. Enormous research uses various data sets, and the diversity of data sets is frequently not assured during data generation. The training package is somewhat comparable and is rarer during training in the rare driving circumstances, where the model will most definitely fail. In order to address this issue, future research should focus on the implementation of reinforcement learning approaches in automated driving.

7. Most driving scenarios are classically believed to be resolvable. The other unsolved solutions are corner cases that need a superhuman driver's judgement and understanding. Deep learning algorithms' generalization capacities should be strengthened to tackle corner cases. In learning dangerous scenarios, generalization in a learning model is crucial, partly because the training data for such corner instances is rare. This also means the conception of one-shoot and low-shoot learning systems with fewer examples of instruction.

8. It is worth noting that the ability of AI mechanisms to adapt based on past experiences has already been demonstrated

to understand the vehicles' control methods parameters, which is a glimmer of optimism. Therefore, an improved approximation of the underlying precise system model shows future research demands of considerable research.

9. In security-critical schemes, the application of protocols depends on learning-based AI techniques currently being debated, bringing closer relationships between computer intelligence and the functional security sectors. The machine learning package is not covered by existing safety standards, such as ISO26262. Despite the introduction of new data-driven layout methods, there are still questions about the stability, explainability, and classification resilience of neural networks and deep neural networks.

10. Many organizations and companies strive for automated driving to find the most effective way of moving from the tentative experimental phase to the commercial phase. Artificial intelligence and machine learning are common methods, and large amounts of data are needed to research using these methods. However, this is dubious as automobile researchers cannot share their resources because they believe their competitive gain would be diminished. In order to solve this issue, core attention is needed to developing policies that will benefit all automated driving research groups get benefits equally and enable them to share their progress easily.

7 Conclusion

In summary, we can restate that have formed a extensive taxonomy that defines all the components of MVCCA in AVs according to the existing protocols and solutions, emphasizing to prevent the collisions between single and multiple vehicles. We focused on the investigations about collision avoidance methods and adaptive driving cooperation challenges. According to the aspects, the strategic scheme was generally grouped. Following that, we reviewed many publications on the stages stated previously and incorporated them into our taxonomy's subsection. After reviewing all of these works, it appears that practical research concerns can be pursued to improve or introduce better versions. A framework of MVCCA in AVs is proposed that is a complete solution provided with the combination of several potential approaches in this field. The recommended technique is expected to increase the performance and reduce the computational cost of the control system that captures the interrelationships of MVCCA components indicated for integrating the learning-based control model into AVs applications. A broad range of topics were explored in the future research issues section to examine the initiatives of leading auto-rotating tool producers, different modern hardware implementation options, and several potential guidelines. It is intended that our proposed system supports further research for assessing and viewing accident prevention technique's patterns in more detail.

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Author contributions statement

A.J.M.M., S.F.B.K. and M.A.R. Conceptualized the Workflow, A.J.M.M., S.F.B.K. and S.A.M. completed the writing, A.J.M.M. and S.A.M. arranged resources, A.J.M.M. and S.F.B.K. completed the formal analysis. M.A.R., M.A.S.K and A.H.A. supervised the work, M.A.S.K and A.H.A. checked the validation. All authors reviewed the manuscript.