Autonomous Cars: Research Results, Issues, and Future Challenges

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***Abstract*—Throughout the last century, the automobile industry achieved remarkable milestones in manufacturing reliable, safe, and affordable vehicles. Because of significant recent advances in computation and communication technologies, autonomous cars are becoming a reality. Already autonomous car prototype models have covered millions of miles in test driving. Leading technical companies and car manufacturers have invested a staggering amount of resources in autonomous car technology, as they prepare for autonomous cars' full commercialization in the coming years. However, to achieve this goal, several technical and nontechnical issues remain: software complexity, real-time data analytics, and testing and verification are among the greater technical challenges; and consumer stimulation, insurance management, and ethical/moral concerns rank high among the nontechnical issues. Tackling these challenges requires thoughtful solutions that satisfy consumers, industry, and governmental requirements, regulations, and policies. Thus, here we present a comprehensive review of state-of-the-art results for autonomous car technology. We discuss current issues that hinder autonomous cars' development and deployment on a large scale. We also highlight autonomous car applications that will benefit consumers and many other sectors. Finally, to enable cost-effective, safe, and efficient autonomous cars, we discuss several challenges that must be addressed (and provide helpful suggestions for adoption) by designers, implementers, policymakers, regulatory organizations, and car manufacturers.**

***Index Terms*—Autonomous cars, driverless cars, connected cars, policy, privacy, security, simulation.**

I. Introduction

VEHICLES were once considered the realm of mechanical engineers. However, the unprecedented advancements in automobiles and information technology have transformed the traditional vehicle from an old-fashioned source of commute into a full-scale, smart, and infotainment-rich computing and commuting machine on the move. If we take a close look at recent advances of the afore-mentioned technologies, we find that the features and characteristics offered by both cutting-edge communication and computing technologies along with the emergence of high-end cars provide the foundation for the realization of smart vehicles. These smart cars are autonomous in that they support features such as sensing the surrounding environment, making quick and timely decisions, navigating without human input on the road, maintaining safe mobility patterns, performing all kinds of maneuvers, and cruise control, to name a few. Such cars have been referred to as autonomous cars. An autonomous car refers to a computer-controlled car that can guide itself, familiarize itself with surroundings, make decisions, and fully operate without any human interaction. The primary drivers behind the emergence of autonomous cars include: the need for driver and driving safety, growth in population, expanding infrastructure, increase in the number of vehicles, the need for efficient time management, and resource utilization and optimization. As the human population grows and the number of cars increases, this creates a stressful impact on our transportation infrastructure, ranging from roads and parking spaces to fuel stations (for fuel engines vehicles) and charging stations (for electric and hybrid vehicles). In the past few decades, governments have taken serious measures for road safety, with many introducing both static and dynamic technologies such as Closed-Circuit Television (CCTV) cameras, road sensors, and more [1]. However, despite these efforts, in the United States alone, road accidents caused more than 32,000 fatalities in 2014. The number of fatalities increased to more than 35,000 in 2015, demonstrating that despite the use of existing technologies, human errors still occur [2]. To minimize human errors and reduce life-threatening situations on the road, alternative technologies such as connected cars and autonomous cars are being explored.

The evolution and emergence of autonomous cars are the result of remarkable research results coming from the fields of wireless communication, embedded systems, navigation, sensor and ad hoc network technologies, data acquisition and dissemination, and data analytics. The idea of autonomous cars started with "phantom autos" in the 1920s, where the car was controlled through a remote control device [3]. In the 1980s, we witnessed the emergence of self-sufficient and self-managed autonomous cars. A major contributor to the autonomous car field was the NavLab at Carnegie Mellon University, where researchers developed the Autonomous Land Vehicle (ALV) [4]. In the same decade, the "Prometheus project," sponsored by Mercedes in 1987 [5], achieved a major result with the design of their first robotic car to track lane markings and other vehicles (nonetheless, for safety reasons, human intervention was necessary). Although it was not fully autonomous at that time, the ability to automatically change

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TABLE I
ACRONYMS AND THEIR EXPLANATION

Acronym	Explanation	Acronym	Explanation
CCTV	Closed-Circuit Television	VANET	Vehicular Ad hoc NETwork
DSRC	Dedicated Short Range Communication	ADAS	Advanced Driving Assistance System
LIDAR	Light Detection and Ranging	GPS	Global Positioning System
ECU	Electronic Control Unit	CAN	Controller Area Network
NHTSA	National Highway Traffic Safety Administration	DoT	Department of Transportation
MaaS	Mobilit as a Service	PROUD	Public Road Urban Driverless car
GPU	Graphics Processing Unit	FPGA	Field-Programmable Gate Array
ASIC	Application-Specific Integrated Circuit	CNN	Convolutional Neural Network
SVM	Support Vector Machine	DNN	Deep Neural Network
LSTM-FCN	Long Short Term Memory Fully Convolutional Network (LSTM-FCN)	IMM	Interacting Multiple-Model
V-2-V	Vehicle to Vehicle Communication	V-2-I	Vehicle to Infrastructure Communication
BRAiVE	Brain Drive	VisLab	Artificial Vision and Intelligent Systems Lab
VIAC	VisLab's Intercontinental Autonomous Challenge	DARPA	Defense Advanced Research Projects Agency
DGC	DARPA Grand Challenge	RNDF	Route Network Definition File
ISO	International Standards Organization	SUMO	Simulation of Urban Mobility
ITS	Intelligent Transportation System	SimLab	Driving Simulation for Vehicle Systems Lab
CARS	Center for Automotive Research at Stanford	CSRC Toyota	Toyota Collaborative Safety Research Center
CAM	Cooperative Awareness Message	NATCO	National Association of City Transportation Officials
RAND	Research and Development	OEM	Original Equipment Manufacturers

lanes was a major breakthrough. In the 21st century, the increasing interest in autonomous cars has been fueled primarily by low-cost, high-performance technologies in various areas. It is important to draw a clear line between two conflicting terms: the automated car and the autonomous car. A bird's eye view of both terms offers a similar concept of enabling a vehicle's independence; however, the former refers to a vehicle controlled through a machine that possibly might need human intervention (for instance, an emergency brake, cruise control, smart park, and so forth), whereas the latter focuses on the actions performed by the vehicle independently without any human intervention.

Autonomous cars leverage the concept of connected car technology [1], [6]. It is worth mentioning that autonomous cars and connected cars share some technologies. For instance, the connected car uses a Vehicular Ad hoc NETwork (VANET) technology where an on-board unit (OBU) is installed on the vehicle; and through the dedicated short-range communication (DSRC) standard protocol [7], [8], vehicles can communicate with each other when they are within their communication range. VANET technology supports two broad categories of applications: safety-related applications and information, entertainment (collectively referred to as infotainment) applications. In the former category, security measures for communication are stringent whereas for the latter, security measures are relatively relaxed.

The applications and services provided by the VANET technology and its successor VANET-based clouds [9], [10] include, but are not limited to, accident warning, crash notification, road construction, traffic signals, ambulance approaching notification, excessive speed, black ice on the pavement, fog warning, traffic information, Internet-on-the-move, movies-on-demand, location-based services, cooperative cruise control, and maneuver control. Most of the afore-mentioned applications and services rely on cooperative communication among vehicles and infrastructure. According to the IEEE 802.11p standard, vehicles share their location information such as position, speed, acceleration, and other control information with their neighbors. Therefore, inter-vehicular communication requires fine-grained input from other technologies such as an accurate positioning mechanism, vehicular sensory information, and efficient and accurate navigation. In this context, world-leading auto manufacturers (along with academic research efforts) have been developing and incorporating a wide range of new features in their high-end cars. The initiatives taken by leading car manufacturers such as Audi, BMW, Toyota, Honda, Kia, Hyundai, Mercedes, Ford, Nissan, Tesla, GM, Volvo, Bosch, and Volkswagen include smart parking, incident warning, emergency braking, and semi-automatic and fully automatic (limited) pilot-driving, all of which have increased competition in the connected car industry. Furthermore, lawmakers are working on legislating vehicle-to-vehicle communication to allow normal consumers to reap the technology's benefits [11]. However, even with the use of advanced technologies, human behavior and driving patterns continue to play a pivotal role in safe driving.

Recent developments in VANET and connected car technologies have attracted the attention of companies such as Google in the development of driverless cars. In addition to Google, car manufacturers such as Tesla and Audi are two leading stakeholders in driverless car technology. Today, we see a strong synergy between technology companies and car manufacturers to enable the design and development of driverless cars. In contrast to Google, Microsoft has set up an alliance with Volvo and Toyota for the development of driverless cars. Similarly, NVidia has also shown a strong interest in autonomous cars by introducing its flagship NVidia Drive PX2, a powerful GPU-based computing platform for autonomous cars [12]. Uber and Apple are also emerging stakeholders in the autonomous car business. In the Asian market, TATA, Yutong, KIA, and Hyundai are major companies investing in the autonomous cars' design, development, and research. For the European auto market, the goal is to achieve a successful realization of autonomous cars by 2020. For instance, Volkswagen recently revealed its V-charge project that focuses on developing autonomous cars. The French PSA group (Peugeot, Citroën and DS) also tested an eyes-off drive from Paris to Amsterdam in April 2016 [13]. Mercedes and BMW are two other leading European companies currently exploring the concept of driverless prototype cars, and they plan to develop full-fledged commercial versions in the near future.

Over the last few decades, the ownership of vehicles has grown exponentially as their costs decrease; also, people find vehicles more affordable as their incomes increase. However, this rate of adoption of vehicles also increases environmental pollution and traffic congestion [14]. In 2010, our planet was host to 1 billion vehicles, and this number is expected to double by 2030; this creates an urgent need for more resources and infrastructure support to host this vast increase in the number of vehicles [15]. According to the World Health Organization (WHO), around 1.25 million people die every year due to road accidents [16], and WHO has projected that the death toll could rise to 1.8 million by 2030 [15]. Therefore, the need for a technologically advanced, fully automated, reliable, and safe means of transportation is imperative, and the autonomous car industry has been striving to meet these expectations. However, because of some high-profile incidents in the past, progress in the popularity of autonomous cars has been impeded, although car manufacturers are still doing their best to address the relevant issues. To be specific, in September 2016, a driverless car collided with a commercial van at a traffic signal that almost hurt the passengers [17]; in another incident, a driverless car's crash cost a passenger's life [18]. A detailed report recently published by the Victoria Transport Policy Institute [19] pointed out that despite the claims and promises made by the automobile industry, it would be difficult to commercialize the purchase of fully autonomous cars before 2035-2040. The Victoria Transport Policy Institute published the latest version of their report in February 2018 which states that the commercialization of autonomous cars will be difficult before 2050 [20].

As previously noted, several important issues remain, such as governments' regulation, consumer satisfaction, market saturation projection, cost, reliability, and safety, that must be fully addressed by relevant parties involved in the autonomous car business. Furthermore, federal regulation also plays a vital role in the success of any new technology, and autonomous cars are no exception. For instance, airbags required a relatively shorter time for full market penetration because of federal regulation. In contrast, the automatic transmission system in cars took a long span of five decades for market penetration, because of its high cost. After almost five decades, the automatic transmission system's quality was improved and the cost reduced to such an extent that it became viable to use in most automobiles. The same arguments hold for electric and hybrid vehicles [21]. In a nutshell, autonomous car technology will take time before it becomes available and affordable to consumers because of its initial high costs and low reliability. Yet vehicle manufacturers must address these issues before they can make autonomous cars a success and transform the automotive industry.

A. *Existing Surveys*

To date, several surveys have been conducted that investigate various aspects of autonomous car technology [22]–[32]. However, to the best of our knowledge, most of these surveys focus on only one aspect of the autonomous car and there is no survey that presents a holistic approach toward autonomous car technology. Our survey spans over last 8 years (2010-date). Campbell *et al.* [22] investigated the real-world autonomous car tests in urban environments and outlined the challenges faced during test drives in detail. Okuda *et al.* [23] conducted a detailed survey on the adaptation of Advanced Driving Assistance (ADAS) in autonomous cars. Fagnant and Kockelman [24] surveyed the policy recommendations and implementation for autonomous cars. Similarly, Bagloee *et al.* [25] discussed some of the challenges related to different policies for the autonomous car. Other function-specific surveys include planning and motion control in autonomous cars [26], long-term maps' constructions for autonomous cars [29] and visual perception in the autonomous car from both implementation and users' perspectives [31], [32]. Furthermore, Abraham *et al.* [27] conducted a survey on consumer trust and their preferences for autonomous car technologies whereas Joy and Gerla [28] reviewed communication and location privacy issues in autonomous cars. Parkinson *et al.* [30] have comprehensively reviewed cyberthreats in autonomous cars. We note that, from the preceding discussion, most of the recent surveys on autonomous cars have mostly focused on specific topics of the autonomous car. Table II presents a summary of these surveys and their differences with our survey.

B. *Scope of This Survey*

In this paper, we present a thorough comprehensive and systematic review of state-of-the-art results for autonomous car technology. We investigate the current existing solutions for autonomous car technology, including its design, applications, testing, and verification. We also discuss in detail the current issues and challenges that have, at least in part, impeded the momentum of autonomous car development. We focus on autonomous car technology's design and implementation issues in detail. Additionally, we investigate both technical and non-technical deployment issues for autonomous cars that must be addressed by all stakeholders in the autonomous car development chain. We summarize the main contributions of this paper below:

1) We present an in-depth comprehensive and systematic review of the autonomous car technology that covers design and implementation issues.
2) We describe state-of-the-art results on autonomous cars from both commercial and research perspectives.
3) We describe in detail design and implementation issues in autonomous cars.

TABLE II
EXISTING SURVEYS

Year	Paper	Topic(s) of the survey	Related content in our paper	Enhancements in our paper
2010	[22]	Test drives in urban environment	Section IV.E	Enhanced list of papers since 2010 to date
2014	[23]	Trends in Advanced Driving Assistance (ADAS) and its adaptation in autonomous cars	Section I	Current state of the art results in autonomous car
2015	[24]	Barriers in autonomous car implementation and policy recommendations	Section IV and VI.D	Separation of design and implementation challenges in detail with a focus on recent results
2016	[25]	Challenges to autonomous car policies	Section VI.D	Holistic approach towards detailed design and implementation challenges covering technical, non-technical, social, and policy challenges
2016	[26]	Planning and motion control for autonomous car in urban environment	Section II.B and IV.C	Coverage of object detection, perception and learning, sensors management, decision-making, and actuation as well as end-to-end functional survey of the autonomous car
2016	[27]	Consumer trust and preferences in autonomous car	Section VI.B.1	Detailed technical and non-technical challenges in autonomous car from design and implementation perspectives
2017	[28]	Communication and location privacy in connected and autonomous vehicles	Section VI.A.6	Detailed security and privacy issues associated with the autonomous car as well as an investigation of possible attacks against the autonomous car
2017	[29]	Building long-term maps for different weather environment conditions in autonomous cars	Section V-B	In-depth discussion of challenges covering several aspects of autonomous cars
2017	[30]	Cyberthreats in connected and autonomous cars	Section VI.A.5	Detailed discussion of security and privacy issues in autonomous cars from attackers', users', and environment's perspectives
2017	[31]	Hardware implementation of visual perception algorithms in autonomous cars	Section IV.A	Enhanced object detection, perception, control, communications, and decision-making in autonomous cars
2018	[32]	Perception of autonomous cars from users' and pedestrians' perspective	Section IV.A	Enhanced user trust with a discussion of the challenges faced by autonomous cars from a consumer perspective

4) We present an in-depth review of different research challenges (technical, non-technical, social, and policy) that need to be addressed by the autonomous car industry.
5) In a nutshell, this paper provides an extensive literature survey on recent research that has been conducted in the area of autonomous car technology and bridges the gap between the design, implementation, and research challenges faced by autonomous cars.

The rest of the paper is organized as follows: Table I lists all the acronyms used in the paper. Section II covers autonomous car technology in detail, including its design, components, and functionalities. In Section III, we discuss the major benefits of autonomous cars, followed by current research results yielded in autonomous car technology in Section IV. The design and implementation issues for autonomous car are discussed in Section V. Section VI outlines the deployment challenges for autonomous car in detail, and we conclude the paper in Section VII.

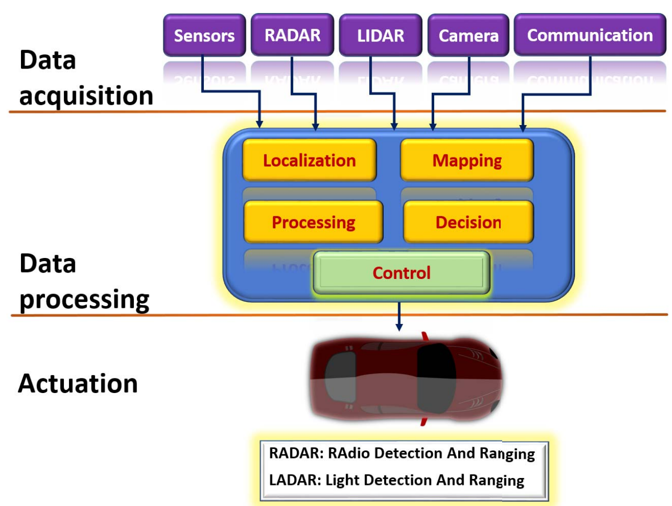

Fig. 1. Autonomous car: functional architecture.

II. The Autonomous Car

The autonomous car has received a lot of attention during the past decade and prototype versions have been developed by different vendors. However, the commercial realization of autonomous vehicles remains a significant challenge. At the very basic level, the autonomous car is equipped with a myriad of sensors and actuators that generate a lot of data in real time that must be processed and analyzed for timely decisions to be made. Therefore, the design of autonomous car must consider the volume, speed, quality, heterogeneity, and real-time nature of data. It is worth noting that different auto manufacturers leverage on-board sensor and actuator technologies for different types of optimized applications. However, at the core of the autonomous car design is the major requirement of being able to function autonomously. In other words, the autonomous car requires features that will enable it to foresee, decide, and move safely and reliably according to some plan. In this section, we outline some of the most fundamental autonomous car design characteristics.

Figure 1 shows the main high-level functional components of a typical autonomous car system. The layered

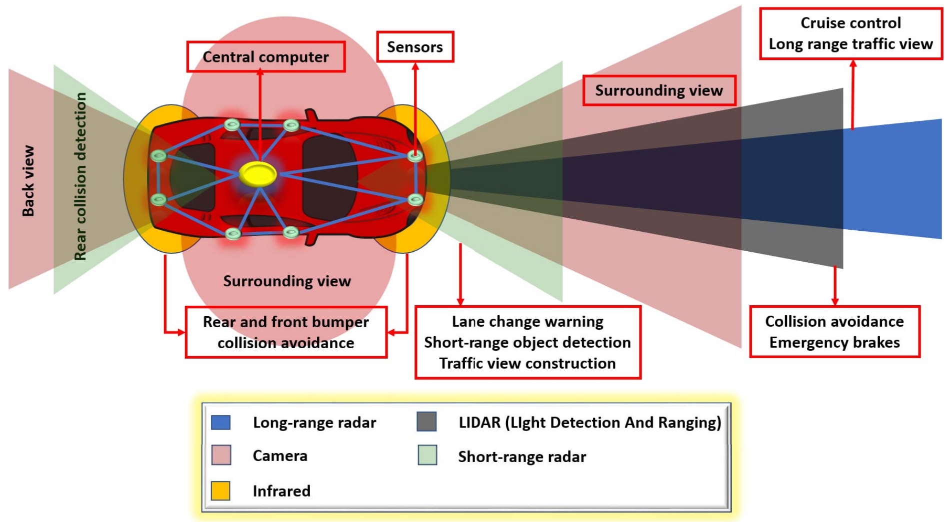

Fig. 2. Autonomous car: system architecture.

structure includes data acquisition performed by the hardware components, such as on-board and in-car sensors; short- and long-range radars; LIght Detection and Ranging (LIDAR) tracking; and cameras and communication devices (transceivers). The data collected through these components is processed by the autonomous car's central computer system, which is then used by the decision-support system. The decision-support system actuates the autonomous car. It is worth noting that situational awareness is realized through both short- and long-range imaging devices that include radar, LIDAR, and cameras. Fig. 2 depicts the areas covered by these components. Different ranges of situational awareness apply to different applications, and they are achieved through different components. For instance, front and rear bumper collision are avoided through infrared devices, whereas lane-change warning, short-range object detection, and traffic view construction are provided by short-range radars. The autonomous car is also equipped with a series of cameras for the surrounding views and LIDAR is used for collision avoidance and emergency brakes. The cooperative cruise control and long-range traffic view construction are achieved by long-range radars. All the aforementioned components are networked and work closely with each other, as shown in Fig. 1.

For an autonomous car to move from point A to point B, it needs to perform a series of steps: the car needs to perceive and make itself aware of the surrounding environment, plan the trip, navigate, and make controlled movements on the road. The primary steps responsible for executing the aforementioned tasks in an autonomous car include:

1) situational and environmental awareness;
2) navigation and path planning; and
3) maneuver control.

We note that the aforementioned steps are iterative from the point when the car starts moving until it has reached the destination. After perceiving the environment, the car needs to get environmental awareness of surroundings, which aids in developing the movement trajectory followed by navigation. In addition to environmental awareness, the autonomous car communicates to several other entities that include roadside infrastructure, neighbors (autonomous cars and contacted vehicles), registration and management authorities, and service providers. The communication paradigm for autonomous car is shown in Fig. 3. It is worth noting that connected car technology has yielded remarkable research results in architecture, communication, applications, and services. Connected car technology is realized through VANETs where vehicles on the road communicate with each other, with the infrastructure and with the environment through different underlying communication technologies such as, but not limited to, IEEE 802.11p, WiFi, LTE, visible light communication (VLC), and so on. Figure 3 shows that the autonomous car communicates with both the infrastructure and its neighbors. It is envisioned that the autonomous car will use the same communication standard which is used for connected car technology today. This will not only ease the integration of the autonomous car with existing connected car technology, but it will also make the deployment of autonomous car communication easier. Finally, the car moves based on the path on the map that it has generated.

A. *Situational and Environmental Awareness*

The first and foremost important step for autonomous cars is neighborhood awareness, which includes object tracking, self-positioning, and lane spotting. More specifically, the car must be able to perceive what is in front of it, and without loss of generality, it also needs 360-degree neighborhood awareness. As we mentioned, several hardware components are used for this purpose, ranging from on-board and on-car cameras to medium- and short-range radars. However, these components have their pros and cons. Cameras are useful for environmental and neighborhood awareness. But the volume and speed of real-time data required for neighborhood awareness is too compute-intensive for vehicular computing. Furthermore, the granularity of data obtained from cameras is inversely proportional to the speed and performance of the decision support

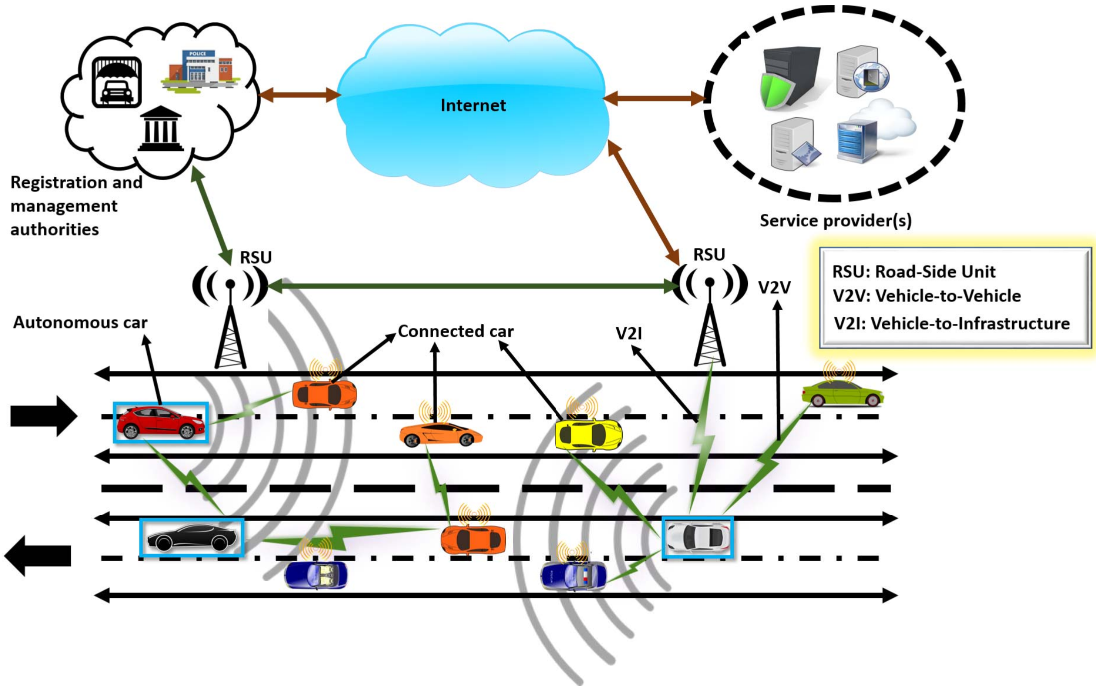

Fig. 3. Autonomous car: different modes of communication and communication infrastructure entities.

system. Therefore, another alternative is needed to enable the perception functionality for autonomous car.

In this context, radar technology has proven to be more efficient in object tracking than cameras, making it a more practical option for vehicles. For the autonomous car, LIDAR tracking is used. The main characteristic of LIDAR includes 360-degree visualization and object tracking with a relatively long range. Therefore, a LIDAR device can be mounted atop the car to get a full view of the surrounding environment. However, it is worth noting that for intensive object detection such as collision-resistance while parking, collision avoidance, and bumper protection, LIDAR does not work efficiently. Instead, optimized radars are installed at the front, rear, and sides of the car for the aforementioned tasks. The data obtained from these devices help the autonomous car's decision-support system maintain speed, apply brakes, change lanes, and maneuver. The data obtained from these devices are also used by sophisticated software to generate a 3D image of the surrounding environment.

B. Navigation and Path Planning

Navigation or guidance is of paramount importance in an autonomous car, because its primary function is to enable the car to travel on the desired path. When the autonomous car is aware of its environment then it needs to plan its path based on the destination. With the help of navigation hardware such as the well-known Global Positioning System (GPS) module, the car generates a path between the current position and destination as a function of time. GPS is the primary source of navigation for the car because of its accuracy, optimized and compact hardware, on-chip design, low cost, and wide range use. Furthermore, the path is dynamically re-calculated in case of certain events such as road block, diversion, and so forth. The car's navigation system must be robust to handle sudden and subsequent changes in the path by adjusting the already pre-computed route. Road networks are physically pre-defined and the autonomous car's guidance system regularly checks the car's movement against the calculated path. It is worth pointing out that although a GPS-based solution provides a rich set of functionalities in guidance and navigation, in certain scenarios, GPS on its own is not sufficient. Since GPS is based on signals from in-orbit satellites, the signals may sometimes get blocked or deteriorated due to natural or artificial phenomena, such as underground roads and tunnels. In such cases, other means of inertial guidance and navigation are needed.

To address this issue, the autonomous car must be equipped with gyroscopes and accelerometers. The inertial method of positioning (i.e., a gyroscope-based solution) does not provide information about the position of the vehicle, therefore the initial position for the gyroscope must be provided either through GPS or entered manually. In the case of autonomous cars, both the gyroscope and GPS can work well together if the context of movement is known. For autonomous cars, GPS information is frequently used as an input to a special map-generation algorithm that uses data acquisition and sensory information acquired from the vehicle. Several research efforts have been conducted and tested on real-world data to generate a map for autonomous cars [14], [33]. The results are promising and will help in the initial commercial deployment phase of autonomous cars.

C. Maneuver Control

After the autonomous car perceives its surroundings, and using this information along with its destination information, then it starts its journey. Different maneuvers should be carefully controlled for a smooth, safe (or at least fail-safe) commute along the road. As we stated previously, the autonomous car is equipped with a large number of different sensors and actuators. Most of the car components are electronically controlled through Electronic Control Units (ECUs). ECUs communicate with each other and with the decision-support system through the Controller Area Network (CAN) bus inside each car. During the course of its journey, the autonomous car must maintain different kinds of maneuvers such as lane keeping, bumper-to-bumper distance, sudden brakes, overtaking, and stopping at traffic lights. These maneuvers need hardware/software support and extensive coordination and real-time data sharing among the car's different control systems.

III. Autonomic Cars' Major Benefits

The concept of the autonomous car, despite its complexity, opens up new innovative applications and presents consumers with safety, ease-of-use, comfort, and value-added services. In this section, we discuss some of the major benefits of autonomous cars and future autonomous car applications.

A. *Improved Safety*

Safety is a multidimensional feature in the automotive domain, where human lives take the highest priority when it comes to driving. In the case of autonomous cars, one of the most important applications is safe driving for its occupants. Every year road accidents claim 1.3 million lives and 50 million serious injuries around the globe. According to the National Highway Traffic Safety Administration (NHTSA) of the United States' Department of Transportation (DoT), 93% of traffic accidents are caused by human errors. The updated report on these numbers was published in February 2015 [34] and stated that 94% of accidents are caused by human errors. Human errors are caused by various factors, including distraction, aggressiveness, carelessness, intoxication, and disabilities. Furthermore, such errors also cost about U.S.$190 billion in health costs and damages caused by these accidents [35]. Based on these alarming statistics, an alternative driving mechanism is essential to save lives. In light of the aforementioned fatalities' statistics with human-driven cars, an autonomous car can be a safer alternative with a lower number of human drivers behind the wheel. Autonomous cars will at least eliminate the likelihood of human errors that account for 94% of traffic accidents.

Another dimension of safety is the car itself. The autonomous car will be equipped with sophisticated technology to authenticate its legitimate users, thereby preventing thieves from stealing the car. With high-tech sensors on-board, the autonomous car can successfully recognize its rightful owner and in case of any unwanted situation, it sends the owner an alert. Although these features, at least in part, are still available in current middle- and high-end cars, nonetheless, the degree of intelligence will improve significantly in future autonomous cars. Furthermore, an autonomous car might not need a key to start like traditional cars. Autonomous cars could operate with biometrics such as fingerprints, a retina scan, voice recognition software, and/or synthetic telepathy. It is worth mentioning that current cars have a fingerprint-enabled door-lock system, but these car operations have not matured enough yet to a level where biometrics can be used.

B. *Business Opportunities and Increasing Revenue*

Mobility-as-a-Service (MaaS) and car sharing are two of the promising applications made possible through autonomous cars without redundant human interactions. The MaaS paradigm [36] will save many consumer resources, including money, time, space, and even human resources (such as drivers). Autonomous cars can be used as a resource instead of owning a car, which will require not only a large sum of money upfront but also a driver and a space to park it. Furthermore, car sharing is a popular application among consumers today. However, with the emergence of autonomous cars, carpooling can become more efficient by utilizing autonomous car resources more effectively. In the last couple of years, carpooling services have garnered much attention among daily commuters for various reasons, such as saving money and time in addition to the hassle of driving that would otherwise make the commute stressful. With traditional carpooling, there are still time constraints when picking up fellow commuters on the way. Furthermore, the cost shared by the commuters may also consider the driver's costs. By using autonomous cars for carpooling services, we can eliminate such costs. This change in perspective will not only create economic advantages, but also decrease air pollution caused by traffic situations in global metropolitan cities. It also creates enormous business opportunities and transforms the mindset of both consumers and service providers.

Autonomous cars will also revolutionize taxi and rent-a-car businesses. Taxi service providers will no longer need drivers, thereby reducing costs and increasing their revenue. Similarly, rental car companies will be able to streamline their business operations with a reduced workforce. Furthermore, such a paradigm shift will also benefit the software industry because of smart applications (such as car sharing, taxi services, and rent-a-car services) that are accessible through personal devices. In short, autonomous cars can help increase revenue and reduce labor costs.

C. *Ease of Use and Convenience*

Another benefit of autonomous cars is ease of use and convenience. Sometimes people are unable to drive a car because of medical/disability conditions or intoxication. Furthermore, the autonomous car can also be a suitable mode of transportation for elderly people, young adults without a driver's license, and people who cannot afford to own a car. In such cases, the autonomous car can provide a safe, cost-effective way to increase citizens' mobility.

D. *Improving Traffic Conditions*

Improving traffic conditions is another major benefit of autonomous cars. Autonomous cars will increase per-vehicle occupancy and decrease the number of vehicles on the road, thereby improving traffic conditions. Furthermore, with human drivers, inter-vehicle distance is a strict parameter to maintain for safe driving. However, with autonomous cars, this distance will potentially decrease, thereby providing more space on the road. By carefully communicating with their counterparts, autonomous cars could perform intelligent fleet management, leading to reduced traffic jams on the roads. Additionally, autonomous cars can also help in adhering to traffic laws more accurately, thereby reducing the need for traffic police officers on the road.

From a different perspective, autonomous cars will also improve fuel efficiency by selecting the best routes [37], which will also decrease air pollution. Fuel efficiency is directly proportional to the way people drive. Different drivers behave differently behind the wheel. Some common driving behaviors include over-speeding, irregular driving, starting and stopping, and sudden braking that decrease fuel efficiency. In this case, the autonomous car can be programmed to use a fuel-efficient mode and avoid erratic driving behaviors that cause fuel inefficiency. Coordination and communication among autonomous and connected cars will also help eliminate tailgating on the road and unnecessary braking situations.

E. Autonomous Parking

Today, parking is one of the major challenges in metropolitan cities because of the increasing number of vehicles, dense population, inter-vehicle distance in parking lots (for passengers and drivers to open the doors without hitting the cars parked nearby), and mismanagement of free parking lots. With the emergence of autonomous cars, autonomous parking will alleviate parking issues. For instance, after dropping off passengers, an autonomous car could park itself even in narrow available parking spaces (whereas humans would otherwise require wider parking spaces for each car). The advantage of this parking approach would save a staggering 6.8 billion yards in United States parking lots alone.

F. Consumer-Centric Experience

Autonomous cars will enable drivers to relax, sit back, and enjoy the ride. In one scenario, the occupants of the car could work while commuting to their workplace or use the car's entertainment system. This gives autonomous cars' designers the opportunity to create immersive passenger-centric experiences that otherwise would not be possible [38]. In another scenario, if the autonomous car is paired with the occupant's mobile phone, a person could ask the autonomous car to pick up kids from school, pick up someone at the airport, and so on. It is worth noting that progress in these areas has already been made by the electric car giant Tesla, which introduced "summon" [39] applications in its high-end models. Summon lets the owner of the Tesla car call it through a mobile application. In other words, the car can go to the designated parking place by itself, such as the basement of a building, and when it is needed, the owner can request the car to be at any designated location. This feature also lets the car owner park it in tight places where it is difficult to exit the car after it has been parked. Furthermore, recent research has been undertaken to better understand different driving patterns, by analyzing drivers' characteristics and behaviors that include gender, age, driving experience, way of driving, personality, emotion, history of accidents, and so on [40].

The aforementioned characteristics collectively mimic the individuals' driving behaviors. Customization of the autonomous car will rely on the knowledge of human behavior. For instance, speed and overtaking during driving on the road depends on human characteristics such as, but not limited to, gender, age, emotion, and preferences. Young drivers tend to drive faster than elderly people, whereas female drivers and elderly people often drive more carefully. People driving with infants and family also tend to be cautious drivers. Some people like to travel on less-busy roads, even if it takes them longer to reach the destination. Therefore, for autonomous car customization, we should take such attributes into consideration. It is also important to consider what the autonomous car does when it is left alone. More specifically, it should park itself in a designated parking lot and it should know when to pick up and/or drop off the owner. The autonomous car's owner should be able to customize it for the various aforementioned scenarios. Autonomous cars will pave the way for a whole range of passenger-centric applications, where passengers can customize their commute experience based on preferences such as speed, level of risk, in-car entertainment, and so on. To be more precise, human characteristics and dynamics will play an important role in determining the ultimate driving experience.

IV. Autonomous Cars: Research Results

In this section, we present current research results achieved in the area of autonomous car technology. We focus on the technological side of the autonomous car and cover key software components and algorithms that include computer vision, deep learning, communication, and control. Before presenting the aforementioned topics, we outline some real-world experiments to assess the feasibility of autonomous cars. Broggi *et al.* [41] described different tests performed (both as individual projects and competitions) on driverless cars between 1990 and 2013. These tests were performed in different scenarios ranging from free road with no traffic to public roads. Furthermore, the results from these tests provide a close insight to the behavior of the driverless cars in different environments. Broggi *et al.* [41] also performed a series of tests on a fully autonomous car on public roads of Parma, Italy in 2013. The authors tested different driving scenarios including traffic lights, pedestrian crossing, freeway junctions, and roundabouts. This test is called the Public Road Urban Driverless (PROUD) car test and was intended to have close insights into the homegrown autonomous car technology. This experiment yielded some very important observations such as the need for extremely detailed and precise maps, efficient learning and perception mechanism. Furthermore, another comprehensive effort was made by Jo *et al.* [42], [43] where the authors applied a distributed system architecture with a focus on the generality of the autonomous car development process without any dependence on any particular development environment. The authors used FlexRay as a communication protocol and software platform to increase the system performance. We note that traditional cars use the CAN bus technology for communication among different ECUs. However, the CAN bus technology has been controversial because of its slow speed and vulnerability to different attacks [44]. Although efforts have been made to enhance the security of CAN bus [45], [46], nevertheless, the speed and difficulty of modifications to the CAN bus continues to hinder its deployment. In contrast, FlexRay is faster and more efficient but expensive. Then, Jo *et al.* tested their implementation of the autonomous car namely, A1, which won the autonomous car competition in South Korea in 2012 [43].

We would like to point out that most of the autonomous car technology is proprietary and therefore inevitably, we focus only on the current research results from both academia and small-scale industry. Next we discuss some research areas which are being explored in autonomous cars.

A. Computer Vision in Autonomous Cars

Object detection and vision are two of the most critical and essential features of autonomous cars. To mimic the human driver behavior, autonomous cars must "see" the road and detect any obstacle in front of and around it, be it another car, pedestrian, vegetation, or any other type of obstacle. These two key features along with other modules enable the autonomous car to drive along the road and respond to any unwanted situation in a safe, or at least fail-safe way, for instance stopping at a traffic signal, slowing down if the preceding car reduces the speed, avoiding running into pedestrians, and so on. To date, many research results have been achieved in both computer vision and object detection for autonomous car. Here, we succinctly outline the current state of these algorithms. However, it is important to mention that most of the currently available pilot versions of autonomous cars use proprietary components and their details are not publicly available. Therefore, we could only report research results that are publicly available.

Janai *et al.* [47] carried out a detailed and systematic survey on the computer vision algorithms and mechanisms used in autonomous cars. They specifically covered the perception, object detection and tracking, motion planning, and end-to-end learning aspects of the computer vision in autonomous cars. Despite significant advances in computer vision algorithms, the errors produced by the latest computer vision algorithms in unpredictable scenarios challenge their effectiveness in the autonomous car [47]. Therefore, the maturity of computer vision in autonomous cars will likely take more time. Furthermore, the complex environments and scenarios faced by autonomous cars during its travel also need behavior analysis and learning mechanisms where the decision support system of the autonomous car can learn and decide in unpredictable circumstances. Therefore, artificial intelligence plays a vital role in the prediction and perception of the autonomous car system. Shi *et al.* [31] also surveyed the current state-of-the-art computer vision algorithms in autonomous cars. They focused on lane detection, pedestrian and object detection, and drivable surface detection. Additionally, they also discussed the currently used hardware such as Graphics Processing Unit (GPU), Field-Programmable Gate Array (FPGA), and Application-Specific Integrated Circuits (ASIC), for the aforementioned functions in the autonomous car. The results from this research revealed that FPGA accelerators enables FPGA to outperform CPU and GPU in terms of energy efficiency, and throughput. However, FPGA incurs slow speed and it takes larger chip areas, therefore ASIC are employed for compute-intensive operations like computer vision. ASICs perform better than FPGAs.

Although computer vision is a vast field that covers many aspects ranging from image acquisition to segmentation and categorization; however, in this work we only focus on object detection, calibration, and motion estimation with some relevance to autonomous cars. Objection detection is a fundamental requirement for autonomous car. The autonomous car must detect both static and dynamic objects to maintain different maneuvers. However, object detection is challenging in autonomous car because of several reasons such as shadows, identical objects, lighting conditions, and so forth. Therefore, the underlying algorithms should take these factors into account. Object detection is carried out with the aid of different sensors ranging from cheap cameras to sophisticated LIDAR and radar. Furthermore, the autonomous car needs sensors for different purposes and types of environment. These include visible light (daytime), infrared sensors (night time or in dim light), and thermal infrared to detect living organisms. A mechanism that combines different sensors to have a detailed, unified, and comprehensive view of the sensed data is called sensor fusion which combines data from an array of different sensors. Recent developments in sensor fusion [48], [49] are encouraging and could be incorporated into the commercial autonomous car technology. More precisely, sensor fusion-based object detection methods offer improved accuracy as compared to the traditional object detection methods.

In another work, Chen *et al.* [50] proposed a deep learning approach to take LIDAR generated data and other RGB images as input and predict a three-dimensional (3D) representation of that data. Chen *et al.* [51] also proposed a convolutional neural networks (CNN)-based mechanism to detect 3D objects with a single monocular camera. They first generate object proposals based on distinct features and then refine them for the identification of true objects. Once the sensory data is available, it is important to classify the object into distinct categories such as vegetation, pedestrian, vehicle, and so on. This process is called semantic segmentation at a pixel level [52]. To address this issue, both machine learning (supervised learning and unsupervised learning), and deep learning approaches have been used for classification. Depending on the available sensory data (whether it is labeled[1] or not), supervised learning model such as Support Vector Machine (SVM) can

[1]Labels are the tags associated with data to provide information about the data. For instance, a label could be a tag that indicates whether the animal is a cat or dog. Labeled data makes data more expressive for the learning.

be used and if the data is not labeled, unsupervised learning can be used [53]–[55]. The aforementioned object detection, semantic segmentation, and classification approaches perform relatively better in terms of accuracy. However, their efficiency is questionable because of the algorithm complexity, incurred computational overhead, delay, and lack of suitable features, and the complexity of designing features manually mandates for other automatic mechanisms. Therefore, deep learning mechanisms are essential for object detection and classification. To this end, deep learning methods such as CNN and auto-encoders are used to increase the performance of the learning and classification process and automate the features design process [56], [57]. In essence, low-level features (such as color and gradient orientation) can be hand-crafted with success whereas mid-level features require some learning and are hard to design by hand [56]. Therefore, it is imperative to automate the process of both low- and mid-level features design.

Construction of a 3D image from 2D image is also an important feature of computer vision that must be incorporated into the autonomous car for motion planning and actuation. The aim of such construction is to have depth in the acquired information in terms of details, particularly in 3D map construction. The most popular and efficient approaches for such construction are deep learning-based approaches [58], [59]. A more comprehensive study of computer vision in autonomous cars is presented in [47].

B. Machine and Deep Learning in Autonomous Cars

Machine learning, deep learning, and artificial intelligence-based techniques are indispensable for autonomous cars. The main reason for the significance of these technologies is the unpredictable environment and behavior of the surrounding objects. As we have mentioned before, most of the computer vision related algorithms and mechanisms such as object detection, perception, scene identification, reconstruction, and estimation use both machine learning and deep learning mechanisms. In this section, we present recent advances in machine learning and deep learning optimized for the autonomous car technology. In addition to the previous contributions of machine learning, software testing is also aided by machine learning techniques in autonomous cars. In traditional software, the operational logic is written manually and tested over a series of test cases whereas in Deep Neural Network (DNN)-based software, the software learns and adapts with the help of large data sets.

Next, we review some of the current popular deep learning models used in autonomous cars. One of the crucial aspects of autonomous cars is perception and it is a good candidate for applying deep learning models. The actuation of the autonomous car heavily depends on perception and therefore, it is important for autonomous cars to mimic the human-like perception capability. Deep learning models also contribute to the processing of massive sensory data in order to make informed decisions. In addition to perception, other functional requirements of the autonomous car that are supported by deep learning include, but not limited to, scene recognition, object (obstacle, car, pedestrian, and vegetation) detection and recognition, human activity recognition, environment recognition, road signs detection, traffic lights detection, and blind spot detection. The popular deep learning models used in autonomous car technology to achieve the aforementioned goals include end-to-end learning, CNN, deep CNN, Fully Convolutional Network (FCN), DNN, belief networks, Deep Reinforcement Learning (DRL), Deep Boltzmann Machines (DBM), and deep autoencoders. Next, we describe the current research results that use the aforementioned deep learning models for different functional components in autonomous cars. Tian *et al.* [60] proposed a DNN-based framework to test the behavior of DNN-driven autonomous cars. The DeepTest implementation in [60] found erroneous behaviors many times while testing the vehicles under different traffic and environmental conditions. This demonstrates the immaturity of the current solutions and the need for more rigorous measures for autonomous cars to be able to function completely independently. Current tests of autonomous cars are relatively controlled.

In principle, computer vision is complementary to machine and deep learning. Most of the computer vision algorithms use machine and deep learning techniques that are used to aid different functional components of the autonomous car such as object detection, scene recognition, obstacle detection, and so on. Chen *et al.* [61] proposed a learning mechanism that automatically learns different features of an image to estimate the proper affordance in autonomous cars. In the proposed mechanism, affordance is estimated for driving actions instead of parsing the individual scenes. This affordance is based on factors such as static or dynamic object on the road, pedestrian, and vegetation. The perception in autonomous cars can be divided into two categories. In mediated perception, the current environment is unknown and the perception-related components are used to recognize important driving-related features such as lane, road, crossing points, pedestrians, and so forth. In the other category called, behavior reflex mode, the neural network is used to train the system based on human behavior which is closely observed and learnt to take decisions for autonomous driving [61], [62]. In addition to these two methods, Chen *et al.* [61] proposed another direct perception method that uses CNNs where they define key perception indicators. The system learns mapping from an acquired image to several affordances related to driving actions such as current steering angle, adjustment with the lane, and staying within the lane. The authors tested their system with TORCS, an open source car racing simulator.[2] Laddha *et al.* [63] proposed a hybrid algorithm based on both supervised and unsupervised learning to detect road features necessary for autonomous driving. A major benefit of this algorithm is that the authors reduced human effort to label the training dataset thereby making it automatic and more scalable. The algorithm takes different types of input data from sources that include OpenStreetMap,[3] different sensors mounted on

[2]http://www.cse.chalmers.se/ chrdimi/papers/torcs.pdf
[3]https://www.openstreetmap.org

vehicle including localization and camera sensors. The algorithm employs CNN to use the generated annotations in the previous steps with the KITTI dataset [64]. Obstacle detection is another important feature for autonomous car. As mentioned before, deep learning can be effectively used to detect obstacles on the road with acceptable accuracy. Dairi *et al.* [65] proposed a deep learning mechanism to detect obstacles on the road based on deep autoencoders and stereovision. In this obstacle detection mechanism, the authors employed a hybrid deep autoencoder that combines the features of DBM and auto-encoders. The results obtained in this work show that the hybrid autoencoder-based solution yields 98+% accuracy (on average) on different datasets, and clearly outperforms the Deep Belief Network (DBN) and Stacked Auto-encoders (SDA).

Another Deep Learning algorithm based on affordance parameters is proposed by Al-Qizwini *et al.* [62] where they take five affordance parameters into account to train the system and perform simulations by using realistic assumptions. According to their results, the direct perception model outperforms the existing mediated and behavior flux models. Xu *et al.* [66] formulated autonomous driving as a future ego-motion prediction problem where multi-modal driving behaviors are trained through an end-to-end Long Short Term Memory Fully Convolutional Network (LSTM-FCN). The proposed architecture is trained by using large-scale video data from vehicular actions provided by an available dataset by the authors. This scheme, in contrast to previous schemes that perform the learning based on mapping from pixels to actuation, employs an end-to-end learning mechanism for improving the learning performance. Furthermore, this algorithm also addresses the limitation of traditional end-to-end learning that is possible only on a specific dataset as in [67]. Xu *et al.* addressed the aforementioned problem by using very large datasets from uncalibrated sources and crowd-sourced datasets and performed learning on those datasets. According to the authors, the learning results were promising because of the deep learning algorithm developed. Although current deep learning models perform well in autonomous cars for different core components, however, it will take time for these models to mature and mimic the actual driving behavior of humans. As a result of recent advances in the popular deep learning architectures such as AlexNet, VGG-16, GoogLeNet, and ResNet, the accuracy of scene understanding and semantic segmentation in autonomous cars [68] have improved. To be more precise, AlexNet is a deep CNN that achieved 84.6% accuracy, whereas another deep CNN architecture called Visual Geometry Group (VGG) achieved 92.7% accuracy. In contrast, GoogleLeNet is a CNN-based architecture and it achieved 93.3% accuracy during the ImageNet Large Scale Visual Recognition Challenge (ILSVRC)-2013. ResNet is a Microsoft architecture that won the ILSVRC-2016 competition with 96.4% accuracy with depth of 152 layers. In the context of these remarkable results from an accuracy perspective, it can be argued that deep learning will play a fundamental role in the future evolution of various aspects of autonomous cars. However, the unpredictability of the driving environment is one of the many factors that is impeding the maturity of these models.

C. Sensors, Communications, and Control

The heart of an autonomous car is its computing unit that implements the logic of the autonomous car in a holistic way. Sensors and actuators play a pivotal role in the realization of an autonomous car system. The autonomy of an autonomous car means handling of both known and unknown environments without any human intervention and needs machine learning, deep learning, and artificial intelligence algorithm techniques as discussed in the previous subsections. These algorithms are data-intensive, and the data is acquired through arrays of different sensors which collectively form a massive sensor network within the car. Therefore, data acquisition, collection, storage, processing, communication among different entities within the car and with the environment, and the control of autonomous car are key aspects that need proper mechanisms. On the other hand, with the removal of human involvement, autonomous cars have to make autonomous decisions based on what is best in a particular circumstance. This characteristic also requires the autonomous car to be more connected to the surrounding environment and draw as much data as it can from neighbors, infrastructure, and the Internet to make the best decision. Therefore, communication is of pivotal importance for the autonomous car. In this context, this subsection considers communication within the autonomous car among different modules, communication between the autonomous car and the environment (including pedestrians and infrastructure) and in-car sensor data analytics.

Autonomous car uses a myriad of sensors that generate a sheer amount of data. The collected data is processed in special ways to get maximum utility. The most common technique is called sensor fusion where data is collected from multiple sensors in an intelligent way to aid the decision support system. To date, different algorithms have been proposed in the literature to deal with various kinds of data in the autonomous car. For instance, Oliveira *et al.* [69] proposed a mechanism to accurately visualize the scene from the 3D data collected through range sensor by using large scale polygonal primitives. The scene visualization is of paramount importance for both perception and learning of the autonomous car. On the other hand, since the scene may change constantly, it is imperative to incorporate a steady mechanism that deals with new unforeseen environments such as obstacles on the road. In this context, the continuous reconstruction of a scene is calibrated with the currently constructed scene and by doing so, the efficiency is increased because only newly obtained data from sensors is processed. The performance parameters for polygonal primitives-based scene reconstruction algorithms consider successful scene reconstruction, and the time taken by polygon detection. Since this method is incremental, and previous data is used in the detection of polygon and reconstruction of the new scene, therefore, when the number of polygons (similar geometrical structures) increases, the time required for polygon detection decreases which in turn increases the efficiency. The incremental scenario representation mechanism is more efficient than other counterparts such as Ball Pivoting Algorithm (BPA), Greedy Triangulation, and Poisson Surface Reconstruction (POIS) where the incremental approach execution time is about 2 to 23 times (on average) less than

BPA, GT, and POIS mechanisms. However, the accuracy of the incremental mechanism is slightly lower than GT since GT produces 0.14 m error (on average) and the incremental mechanism produces between 0.83 and 0.98 m error. Therefore, the designers of the autonomous car's object detection modules must take these results into account.

Similarly, road detection is one of the key requirement of the autonomous car and is usually realized through different sensors such as on-board camera and LIDAR. Since these sensors exhibit different requirements, sensor fusion techniques are used to harness the features of both. Xiao *et al.* [70] proposed sensor fusion techniques using LIDAR data for road detection. The authors used a variant of Conditional Random Field (CRF), known as Hybrid CRF (HCRF), to harness the advantages of both LIDAR and camera sensors. This model uses a binary labeling mechanism where 'road' or 'background' are labeled. In using such multi-modal approaches, it is necessary to align the pixels from the camera with LIDAR point cloud. The proposed HCRF was evaluated on different datasets and the authors showed that the maximum F1 score (F1 score or F-score refers to the degree of accuracy in terms of precision and recall) for HCRF is roughly 3% higher than the point classifier and point-wise CRF. It can also be argued that the combination of camera and LIDAR sensors provide efficient detection with maximum utility if the features of both of them are fully utilized. Similarly, vehicle localization is also one of the important functional parameters for the autonomous car and is therefore achieved through data from multiple sensors that include GPS, gyro, speed sensors, accelerometer and so on. Additionally, data fusion techniques are also used to correct the errors of the traditional GPS systems [71]. During the development of the autonomous car, Jo *et al.* [42], [43] used the Interacting Multiple-Model (IMM) fusion algorithm for localization. The algorithm is based on adaptive filters in order to deal with different road conditions [72]. Jo *et al.* [43] used existing algorithms for different functional components of the autonomous car including perception, localization, planning, communication, and actuation. To this end, we described sensor fusion algorithms that deal with in-car sensors and communication systems. In addition to the communication inside the autonomous car, communication of the autonomous car with the outside world is also crucial for its operation. Next, we describe different algorithms and schemes that discuss communication among autonomous cars and other entities.

Connected vehicles and autonomous car technologies are often considered as separate technologies but in fact they are orthogonal to each other. Efficient coupling between these two technologies reinforce their synergies towards better realization of the intelligent transportation system. Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications enable cars to cooperatively communicate with each other and with infrastructure hardware devices such as RSUs to support a plethora of applications [73]–[75]. The cooperation among vehicles and infrastructure can be extended to different applications such as cooperative platooning applications [76] where cars exchange their mobility data to enable platooning, and cooperative traffic information system where cars share their scheduled beacons to construct traffic views [77]. Similarly, autonomous cars can cooperate with each other as well in different capacities. For instance, sharing sensors' data with the neighbors will not only help neighbors in different situations such as maneuvers, but will also make driving safer. More precisely, cooperation among autonomous cars can have many other benefits that are critical as well. For instance, cooperative state estimation with trajectory information sharing among autonomous cars can make navigation more effective and smoother as well as help autonomous cars if one of its subsystems fails. Other applications of cooperative communication among autonomous cars include cooperative localization through optimized sensor configuration and motion coordination [78].

Hobert *et al.* investigated cooperative autonomous car applications and discussed the protocols that are used for cooperative communications. Furthermore, they also suggested amendments to the existing standards such as IEEE 802.11p so that it meets the additional communication requirements of the cooperative autonomous car such as additional vehicle status data, convoy management, maneuver negotiation, intersection management, cooperative sensing, high message rate, low end-to-end delay, and enhanced reliability [79]. Cooperative autonomous driving also aids in platooning where autonomous cars coordinate, share information about surrounding environment, and maneuvers to operate safely. Efficient, timely, and effective communication is needed in platooning applications of the autonomous car because platoon members must be in constant contact to adjust and maintain their maneuvers. Peng *et al.* [74] analyzed the performance of IEEE 802.11p protocol used for communication among platoon members. Furthermore, multi-platoon communication is also important for platooning. Peng *et al.* [74] considered inter-platoon communications and found out that first and last vehicles of platoons affect the communication among different platoons. The authors also concluded that IEEE 802.11p effectively supports platooning applications in autonomous vehicles. Numerical results revealed that fine-tuning of parameters such as contention window size and maximum back-off time contribute to the overall performance of IEEE 802.11p in terms of retransmission probability, network throughput, packet loss, and end-to-end delay. Since the communication is carried out among the platoon leaders, therefore sharing cooperative awareness information is effective and the end-to-end delay is reduced (in the experiments, it ranged from 1 ms to 2.5 ms), which is an acceptable range for vehicular networks applications. In short, IEEE 802.11p standard, after necessary tweaks, has the capability to be used as communication mechanism for cooperative autonomous driving. However, currently there are other available choices for autonomous car platooning applications. For instance, cellular-based communication mechanism is also used for platooning applications in autonomous cars. However, resource allocation in cellular networks is a challenge and must be carefully handled. Peng *et al.* [75] proposed a LTE-driven, subchannel-based resource allocation mechanism for inter-vehicle communication within a platoon and among platoons.

In autonomous car platoon communication, the required information is not limited to cooperative awareness, but also platoon management, such as joining and leaving the platoon, and so on. This work considered LTE instead of other existing technologies to reduce the communication delay among vehicles. The experimental results of the proposed scheme demonstrate its effectiveness in terms of end-to-end transmission delay, power control, and the average transmission power required for communication. The results show that for platoon sizes between 3 and 20, the end-to-end transmission delay incurred by the proposed scheme is about 1 ms which is about half the delay incurred by Device-to-Device (D2D) unicast algorithm. It shows that the proposed solution can effectively manage different platoon sizes. Apart from afore-mentioned communication technologies, Visible Light Communication (VLC) is also used in connected car environment with perfect line of sight where transmitters and receivers are installed in the headlights and tail lights of the cars [80]. VLC uses visible light for both illumination and transmission of data in wireless networks. However, VLC is still in its infancy and efficient channel modeling is essential for it to meet the requirements of connected car and autonomous car applications. The massive amount of data produced and processed by the autonomous car also affects the current available network bandwidth. Therefore, researchers are investigating novel techniques to meet the demands of bandwidth for autonomous cars. Kong *et al.* [81] discussed the feasibility of using mmWave in autonomous car communications to share different types of data about the surroundings and the environment in real time.

Autonomous cars also communicate with pedestrians for cooperative motion planning. Chang *et al.* [82] proposed a communication mechanism between pedestrians and autonomous cars called *Eyes on a car*. The autonomous car makes an eye contact with the pedestrian while he/she crosses the road and assesses the intention of the pedestrian. Based on the perceived intention, the autonomous car takes the decision whether to stop or cross the road. In this project, real-world users were tested with the prototype and their decisions about crossing a road were observed. According to the results, 86.6% of the users made a correct decision whether to cross the road or stop. Furthermore, it was also observed that the users made street-crossing decision 0.287 seconds faster than in the case where there was no "eyes on the car". This difference in decision making is significant for both passengers' and pedestrians' safety. Although the research is still preliminary, it is a good starting point to address the issue of consensus among pedestrians and autonomous cars on the roads without traffic lights. It is also important to know how humans react to autonomous cars while crossing the road. Rothenbücher *et al.* [83] designed a social experiment where they hid the driver with a costume and installed fake LIDAR and other necessary equipment on the car to look like a real autonomous car. The experiment revealed that about 80% of the participants in the experiment believed that the car was driving itself. The goal of the study was to obtain data on user reaction to autonomous car which will eventually help autonomous car designers to design better interaction systems for users.

Control is another distinctive feature of the autonomous car that provides guidance along the planned path. In other words, autonomous vehicle control is a module that controls the behavior of the autonomous car in different situations and environments and guide its execution [84]. Moreover, control also refers to a hardware level component that converts the intentions generated by different software modules into actions performed by the hardware. For instance, when trajectory is planned for autonomous car, the control module must make sure that the autonomous car takes that trajectory during motion and handles both predicted and unforeseen circumstances. Jo *et al.* [43] developed a two-level control system for the autonomous car, lateral control and longitudinal control. Lateral control is related to the steering wheel where the control algorithm calculates the steering angle for the next action based on the generated path. It is worth noting that preview points and lateral error of those preview points from the generated path determine the accuracy of the steering wheel angle. The worst case results show that the execution time of the vehicle control module is 3.14 $msec$ on an industrial computer. This execution time is calculated based on the home-grown implementation of the software modules described in [43]. In contrast, the longitudinal control algorithm is related to the acceleration level of the vehicle and the brakes status. This control module takes care of the speed, distance, and emergency brakes. The control generates discrete velocity based on any two or given points. In addition to these two types of control, autonomous cars also use a model for predictive control. This model aims to optimize the predicted motion of an autonomous car [84]. It is also worth mentioning that some authors consider control in terms of communication delays and render it as aiding mechanism for inter-vehicular communications [85].

To this end, since the autonomous car deals with massive amounts of real-time data and in the case of platooning applications, autonomous cars must communicate with neighbors and with the surroundings in real-time; therefore, we need to make the control mechanism of the car efficient enough to stabilize the operation of the platoon. The communication delay plays a pivotal role in communicating among vehicles of a platoon or among different platoons. On the other hand, wireless communication is prone to communication errors and unexpected delays. Thus, autonomous cars must have a robust control mechanism to deal with the transmission delays of the wireless communications among vehicles. Zeng *et al.* [85] proposed an integrated control mechanism for autonomous vehicle platoons. In this control mechanism, the authors analyzed the communication delay boundaries to determine the stability of the platoon. The authors also determined the upper bounds of the transmission delay that is acceptable for the platoon operation. With the modeled adaptive control mechanism, Zeng *et al.* enhanced the reliability of the communication mechanism of the platoon-based autonomous cars. Another aim of this work was to analyze the stability of the platoon system in different environments. In particular, plant stability (when the leader decides the moving speed and distance between the cars and these parameters are maintained by the platoon members) and string stability (when any disturbances in the movement of preceding vehicles will not increase) are analyzed by the authors. Based on these stabilities, the authors derived the maximum delay that can be tolerated by the platoon in order to function normally.

Control in autonomous car is different from conventional control system. In case of autonomous car, different control systems must interact in autonomous car to deal with the unpredictable environment and thus-forth reaction of autonomous car to the environment [86]. In other words, the central control system of autonomous car depends on the context which advocates for an adaptive control system. However, knowledge of the context is essential for the control system to act accordingly. To this end, there are various methods to learn the context from the environment, for instance cooperative communication. Liu *et al.* [87] leveraged beacon-based communications among vehicles in a platoon and with the vehicles that are part of the platoon. Although this work only focuses on connected cars, such joint control-communication mechanism can enable the autonomous cars to react and adapt to different road environments in both platoons and individual autonomous cars.

D. Decision Making

Decision making in increasingly complex and uncertain environments is the pinnacle of autonomous cars. Cars that usually focus only on their local environment and do not take into account, what is going on around them, are referred to as "ego-vehicles" as they consider only their current status, speed, direction, and destination and so on [88]. It is also worth noting that with the advancements in vehicular networks and autonomous cars, the concept of ego-vehicle is slowly fading away because of the need of communication among autonomous cars and the environment. In the previous sections, we discussed different prediction algorithms and techniques that are essential for the computer vision part of the autonomous car. These algorithms and techniques produce predictions with a high probability. However, the final decision is taken after considering the predictions based on the sensory data and input from other modules. Another challenge for decision making is the occlusive and uncertain environment that affects the prediction, and ultimately the decision making process. Such occlusions are caused by noise in sensory data, unpredictable behavior, limitations of sensors, and most importantly the hidden state of the neighbors [89]. In order to make prediction with the highest probability, the autonomous car system must have fine-grained information about the neighbors. However, in some cases, such information about the neighbors may not be public or may not be shared. This constraint poses serious problems for autonomous car prediction and perception modules that directly affect decisions. The fact that human behavior impersonation in autonomous cars is extremely difficult, and as result, the decision making process becomes even more challenging. To this end, the decision-making problem is multi-dimensional and depends on various other elements such as autonomous car's behavior, perception and prediction, neighbors, sensor data processing, components' calibration, and so on.

Existing decision-making mechanisms in autonomous cars can be categorized into machine learning, deep learning, artificial intelligence, multi-policy decision making, and Markov decision process [89]–[92]. Although efforts have been made to make the decision-making process of autonomous cars reliable but there are too many external factors to address all the issues. Therefore, decision making needs to be addressed in a holistic way by the research community by taking into consideration the potential of inter-vehicular communication. As mentioned before, ego-motion of autonomous cars will hinder the growth of autonomous car technology. Therefore, inter-vehicle communication can play a crucial role for cooperative crowdsensing, crowd-perception, and neighbors' behavior. In this context, the communicating nodes (autonomous cars, ordinary cars, and other entities such as pedestrians) will not only share information with each other, but also the perception and driving decision which will strengthen the capabilities of the decision-making process. The decisions made in such a cooperative manner will have global impact on the surrounding traffic rather than making the individual trip of an autonomous car secure.

Connected car technology [1] will play an important role in the commercialization of autonomous cars in the future. Connected car technology has been extensively researched and the applications of connected car technology can already be seen in today high-end cars. In essence, connected cars leverage both cars and infrastructure as communication entities. Furthermore, recently the integration of connected car with cloud infrastructures has also resulted in new applications that use cloud services [9]. It is imperative that the autonomous car leverages the benefits of cloud in different ways such as the execution of sensor fusion algorithms, generating detailed map, system diagnostics, history catalog, and other resource-hungry machine and deep learning algorithms [14], [93]. However, the communication delay incurred by the communication between the autonomous car and the RSU and/or cloud infrastructure make this approach less attractive for critical functions of the autonomous car. In this context, the decision-making module of the autonomous car cannot tolerate any delay from the RSU or the cloud infrastructure. Therefore, the role of the cloud infrastructure, at least at the moment, is limited to value-added services and long-term behavior analysis of the autonomous car whereas decision-making is carried out locally at autonomous car in real time. In addition to cloud computing, fog computing that extends the cloud paradigm to the edges of the network, may be leveraged to provide real-time services requiring low delays [94]. Some researches have already envisioned fog-based vehicular networks and vehicular clouds [95], [96] that can be extended to autonomous cars in connected environments.

E. Real-World Tests of Autonomous Cars

To date, many real-world tests have been conducted to assess the operation and performance of autonomous cars. Here, we outline some real-world tests about the autonomous car next.

Campbell *et al.* [22] participated in the DARPA Grand Challenge (DGC) for autonomous cars. DGC was announced to collect the results of real world autonomous car tests and it consisted of 3 rounds. The authors documented their experience and lessons learnt from the tests. In essence, Campbell *et al.* implemented the autonomous car technology in an ordinary car consisting of the necessary equipment to enable the car to drive itself without any human intervention. The competition was mission-based and a Route Network Definition File (RNDF) was provided to the autonomous car to drive itself through the provided map and through the road structure. The home-grown autonomous car system consisted of traditional components such as sensing, perception, planning, and control. These real-world tests gave more insights to Campbell *et al.* [22] regarding the issues that need to be resolved, should the autonomous car technology become commercial. Some other researchers also described their experiences with the autonomous car and documented important insights to the problems that still need to be solved for the fully autonomous car. For instance, Endsley *et al.* [97] studied the Tesla Model S autonomous car for 6 months from different perspectives such as assessing the situation awareness, adaptation with the autonomous car, reaction to unforeseen circumstances on the road and so on. The study concluded that some of the pressing challenges faced by the autonomous car industry include consumer mental model development, trust in autonomous cars, environmental complexity and interfaces/design for the occupants. Although this study is based on a personal and individual experience, it does provide important feedback from a real consumer perspective.

Broggi *et al.* [98] developed and tested BRAin driVE (BRAiVE) at Artificial Vision and Intelligent Systems Lab (VisLab).[4] A series of tests were conducted on a locally designed autonomous car that traveled 13000 kilometers from Italy to Shanghai. During this expedition, the VisLab's prototype came across many unknown environments and the developers of the project had a chance to analyze the effectiveness and performance of the prototype model. This expedition was referred to as VisLab's Intercontinental Autonomous Challenge (VIAC). This test provided a large amount of real-time data that is currently being used to upgrade the autonomous cars with new functionality and improved their performance. However, VIAC worked on the leader-follower principle due to the unavailability of fine-grained maps. Therefore, one of the serious limitations of VIAC was its dependency on a leader to let the followers know the coordinates for the entire itinerary. Later on, in 2013, Broggi *et al.* [41] took the VIAC experience to another level by testing the autonomous cars on streets. The project called PROUD not only addressed the issues with VIAC, but also traveled faster than VIAC. Although the PROUD test achieved its targeted results, it also revealed that the driving efficiency, speed of the autonomous cars and perception in many-lane roads must be further investigated.

Jo *et al.* [42], [43] developed an autonomous car from scratch and carried out extensive experiments on the prototype model of the car. The results are based on the outcome of an autonomous car competition held in South Korea in 2012. Jo *et al.* designed the architectural framework of the autonomous car and tested it through different environments. The software architecture for automotive products is an important component that is responsible for the normal functioning of the ordinary car and for the maneuverability of the autonomous car. Among other software architectures, AUTOSTAR [99] is an open standard architecture used by many automotive manufacturers. However, for research projects, AUTOSTAR is too expensive and too complex to implement. Therefore, a lighter version, namely, AUTOSTAR-lite, was proposed in [100]. Jo *et al.* used the lighter version of AUTOSTAR for their autonomous car software. With extensive experiments on the autonomous car developed, the authors favor a distributed approach for the autonomous car architecture over the centralized approach where functional components of the autonomous car are grouped together into several local computing units. The rationale behind distributed architecture is to deal with the complexity of autonomous car algorithms. Distributing the computational load into multiple local computation units not only increase the efficiency, but also improves the performance and enables parallel computations.

Apart from academia, the automotive industry has also taken initiatives to involve potential consumers in autonomous cars tests in the real-world scenario. For instance, "Drive Me"[5] is a unique project started by Volvo where the company planned to distribute about 100 vehicles among consumers in Sweden to collect the data from consumer about their daily routines [101]. Furthermore, the goal of this project was to investigate the driving behavior, consumers' preferences, and other important dynamics of driving. The project's goal was to get the consumer perspective of the technology and obtain as much data as it could for research purposes. It also planned to use this data for improving the quality of life when commercial autonomous cars will hit the road in the near future.

V. Autonomous Cars' Design and Implementation Issues

The future of autonomous cars will be decided by their safety, robustness, graceful degradation, fail-safe nature, hardware/software designs, and consumer satisfaction. However, to achieve these goals, the design and implementation of autonomous cars need to provide extreme precision, safety, and reliability, because human lives directly depend on them. The autonomous car relies on major technologies such as LIDAR, radar, positioning, sonar, sophisticated sensors, and optimized software. In this section, we outline the design and implementation issues faced by the autonomous car industry. We also present current validation tools (including simulators) used to simulate and test various aspects of the autonomous car.

A. Cost

One of the major hurdles in the mass production of autonomous cars is the cost of hardware and software. From a hardware perspective, LIDAR costs around U.S.$75,000, which is far more expensive than the car itself. Therefore, it

[4] http://vislab.it/

[5] https://www.volvocars.com/intl/about/our-innovation-brands/intellisafe/autonomous-driving/drive-me

is reasonable to assume that hardware costs will play a crucial role in autonomous cars' design and deployment.

B. Maps

The maps used by autonomous cars are different from the maps generated by traditional GPS systems. These maps use a lot of road details such as lane dimensions, distance from pedestrians, and curb height. To store all these details, an autonomous car needs enormous memory and processing power (the memory and power needed also are directly proportional to the length of the road). It is also worth pointing out that the autonomous car logs every mile of the road it travels. A detailed survey about localization and mapping in autonomous cars is carried out by Bresson *et al.* [29]. The authors both focus on building maps in different weather conditions and environments and reusing the built maps. However, as afore-mentioned, building such maps require enormous computational and storage power. To handle such large volumes of data in real time, we need advanced storage and processing capabilities in the autonomous vehicle. Leveraging big data solutions to address this challenge might be one option to explore in the future [14] According to statistics [102], in California alone, the road network spreads about 170,000 miles, and in the United States, there are 4 million miles of public roads. Logging the data for the whole country, and then inter-country, would be an immense challenge. Some efforts have already been made to draw precise maps based on the data acquired by different sensors such as 3D LIDAR, odometry sensor, and low cost GPS; however, the changing environments and road structures are still challenging for efficient mapping [103].

C. Software Complexity

The final decision of whether to get the car moving, stop, perform a lane change, overtake, and so on is taken based on the output of a software program that runs the autonomous car. Therefore, the accuracy of the results delivered by such a software program must be highly reliable. As we mentioned previously, a huge amount of data, collected from the environment and surroundings through different sensors, is used as input to the software. The real-time processing and analysis of such data remains a challenge for the autonomous car. To date, test drives of autonomous cars have shown, by far, good results in terms of reduced dangers per mile and the reduced number of disengages [104]. It is worth mentioning that at the moment, most autonomous car companies include a "disengage" functionality into their driverless cars during the test drive, which enables the reserve driver to disengage in case of any incident. However, autonomous cars have still to be tested in more hostile environments such as fog, heavy storms, at night, and massively crowded cities. To date, autonomous cars have been tested on highways and urban scenarios. The data also are logged for further processing and behavior learning. On the back end, autonomous car software implements learning algorithms to record the driving patterns and behaviors of the car, such as response to obstacles on the road, pedestrians crossing the road, overtaking, giving way, and so on, and later on the autonomous car uses the learning experience in future situations. Obviously, timely updates, tweaks, and integration of this software with other in-car software will be critical to the autonomous car's performance and security.

D. Simulation

One of the cheapest means of validation of a technology and/or design is simulation. Autonomous car designers are particularly interested in improving self-driving technology because after rolling out the technology, there is no margin for errors. Today, Google is leading the autonomous car market with hundreds of prototype cars [6] that are logging the driving experience using specialized software running inside the cars' computers. These prototype autonomous cars have already completed millions of miles and have been re-driven to make sure everything runs well. Furthermore, there have been experiments conducted on real-world cars to check the dynamics of the autonomous car systems [105]. The idea behind such a large-scale simulation is to make sure that the software functions works reliably and safely. Most simulation tests of autonomous cars are performed on real hardware (i.e., prototype cars) with all the built-in functionalities essential for autonomous cars, with test drivers behind the wheel. However, reasonable efforts have been made to test autonomous cars' functionality through existing simulator tools that simulate different aspects of the autonomous cars, including mobility dynamics, path testing, fuel economy, path planning, and so forth [89], [106]–[113].

In essence, traffic simulators are used to test various aspects of driving including mobility, behavior, traffic scenarios, and lane keeping. Traffic simulations can be divided mainly into two classes: macroscopic and microscopic simulations [114], [115]. Macroscopic simulation models cover the abstract level of details about the traffic situation derived from most of the vehicles in use. In contrast, microscopic traffic simulators model the individual vehicles' behaviors. Both models have their pros and cons. For instance, macroscopic models are fast and require fewer resources, whereas microscopic simulation models require more resources but provide better granularity in terms of understanding the behavior of individual vehicles. Furthermore, because microscopic simulation deals with individual vehicles, the simulation must be run many times to obtain the required accuracy. There are many traffic simulation tools that provide either one (METANET – a macroscopic simulator [116], VISSIM [117], PARAMICS [118], CORSIM [119], and Transportation Analysis and SIMulation System (TRANSIMS) [120] – microscopic simulators) or both simulation models (Simulation of Urban Mobility (SUMO) [121] incorporates both macroscopic and microscopic mobility). In the case of autonomous cars, the vehicle's behavior is tested with these simulators. We note that in the simulation environment, real-world scenarios are oversimplified to cope with computers' resource constraints. It is difficult for the simulators to capture all the details of actual, large, complex road networks. Simulating kinematic behavior, sensors' data processing, and

[6]https://waymo.com/

motion behavior of the autonomous car is still a challenge for current state-of-the-art simulation tools. Next, we present the simulation tools used for validating and testing autonomous cars' behaviors.

Figueiredo *et al.* proposed an architecture to incorporate the autonomous car behavior analysis into an existing microscopic traffic simulator such as MAS-T^2er Lab's simulator [106], [122]. They included data fusion from sensors as well as realistic kinetics of the vehicle while on the move, visualization of simulation models, inter-vehicle communication for different purposes, and so on. The authors used MAS-T^2er Lab's microscopic traffic simulator and built a system on top of the existing simulator to incorporate different functions of autonomous cars. MATLAB is a powerful tool used for simulating scenarios in different fields of computer science, including networks. Autonomous car uses different data acquisition systems, including vision, radar, ultrasound, and a variety of different sensors, to assist different tasks such as steering, braking, acceleration, and deceleration. Engineers at MathWorks designed a simulation environment in MATLAB and Simulink for an ADAS [123]. The strength of MATLAB and Simulink is that they provide engineers in industry and academia with a rich set of functionalities such as design and test vision, radar, and a LIDAR reception algorithm, data acquisition and sensor fusion algorithms, simulation of a driving environment, vehicle model, and driver models. In a nutshell, MATLAB provides a comprehensive suite of algorithms used for testing autonomous cars. Furthermore, the simulation environment meets ISO 26262,[7] requirements.

There are different platforms for simulating the various aspects of autonomous cars. For the physical car itself, classical engineering tools could be used that would incorporate testing of the sensors, vehicular dynamics, controller design, actuators, and so on. These tools include CarMaker,[8] PreScan,[9] Simulink,[10] and many more. Many application-specific tools also can be used to simulate traffic management, car-following, lane changing, and cruise control and to create a realistic environment for autonomous cars. Additionally, these tools are used to determine the effect of overall traffic scenarios on autonomous cars. Another such simulation tool is MATSim,[11] an open source tool that provides a framework to simulate large-scale, agent-based transportation networks [125], [126]. MATSim simulates the road network scenario for one day with different agents. In the context of traffic simulations, agents are the nodes classified into different categories such as public transport, private transport, taxis, pedestrians, and so forth. These agents have specific attributes assigned to them and they share data according to these attributes during simulations.

Other well-known microscopic simulation tools that address the traffic dynamics such as road conditions, driving behavior, traffic conditions, and inter-vehicular communication from a single vehicle perspective have also been used. TRANSIMS is an integrated simulation system used for transportation analysis.[12] It supports traffic modeling, scenarios generation, activity generation, and estimation of emissions based on simulation results. TRANSIMS is based on cellular automata, where the underlying models are discretized based on time and space. Furthermore, each link in the simulation is divided into fixed-size cells and the cell could be occupied by a car or empty. Usually the cell's length is a function of the car's average size. Due to the fact that cellular automata-based models are relatively simple to implement, they are computationally effective and can simulate large-scale networks.

Simulation of urban mobility (SUMO) is a microscopic simulation tool that simulates behaviors on a per-vehicle basis. SUMO is free, and it was developed by the German Aerospace Center (DLR). SUMO is based on two mobility models: Krauss and Gipps models [115], [127]. The functional architecture of SUMO is based on a continuous time-discrete approach and it also allows the modeling of the intermodal traffic system, including vehicles, public transport, and pedestrians. SUMO is a rich tool that supports route finding, network import, and emission calculation in addition to the possibility of enhancement with custom models. SUMO also provides various application programming interfaces (APIs) to integrate with different systems, and it can import road networks in different formats from map databases such as OpenStreetMap[13] and other simulators such as Visum,[14] Vissim,[15] and NavTeq.[16]

For simulations concerning the vehicle and its mechanical dynamics, classical simulation tools such as (veDYNA, CarSim, NS2, NS3, OMNET++, OPNET, NcTUNs) are used for simulating sensors, vehicular dynamics, controller design, data acquisition, and dissemination techniques. Specific application-based solutions such as traffic-management applications that surround vehicles also exist to enhance simulation tools. Such tools are used to create a near-realistic environment for autonomous cars' testing and to evaluate the impact of the surrounding environment on autonomous cars and vice versa. Vissim is a commercial traffic simulation tool developed by PTV.[17] Vissim has a rich set of features that includes graph-based structures for representing nodes that include vehicles (both private and public transport vehicles and trucks), cycles, pedestrians, rickshaws, traffic lights' management, and so on. The signatory features of Vissim include simulation of pedestrians, motorcycles, and bicycles that are rarely implemented in microscopic simulators. Additionally, Vissim also provides a high level of visual details through 2D and even 3G graphical user interfaces. To date, Vissim has been used to evaluate many traffic scenarios, such as analysis of mixed traffic flow

[7] https://www.iso.org/standard/43464.html KAFKA20122

[8] https://ipg-automotive.com/products-services/simulation-software/carmaker/

[9] https://www.tassinternational.com/prescan

[10] https://www.mathworks.com/products/simulink/?requestedDomain=www.mathworks.com

[11] http://matsim.org/

[12] https://sourceforge.net/projects/transimsstudio/

[13] https://www.openstreetmap.org/#map=3/69.62/-74.90

[14] http://vision-traffic.ptvgroup.com/en-uk/products/ptv-visum/functions/

[15] http://vision-traffic.ptvgroup.com/en-uk/products/ptv-vissim/

[16] https://here.com/en/navteq

[17] http://company.ptvgroup.com/en/home/

for speed control [128], speed control and cruise-control [129], and to check the constraints of connected vehicles [130], to name a few.

The growing interest in autonomous cars has also led to the development of several testing platforms such as SimLab, ProspectSV's Intelligent Transportation Systems (ITS) Lab, and MIT Media lab's Moral Machine.[18] One such leading testing platform is called the Driving Simulation and Vehicle Systems Lab (SimLab). SimLab was developed at fkaSV (a subsidiary of German company fka) and provides access to new startups for autonomous car technologies to test their solutions that include algorithms for autonomous cars, behavioral testing, application testing, and communication testing. SimLab offers advanced features for simulating autonomous cars. Unlike other driving simulators, SimLab offers paid autonomous car simulation services to clients at the testing site in Silicon Valley. Clients can test their applications in the autonomous car environment and SimLab provides the integration environment. SV SimLab is one of several other driving simulators owned by the company fka (ForschungsgesellschaftKraftfahrwesen mbH Aachen). [19] It is worth noting that fkaSV is a collaboration between the startup incubator ProspectSV and fka at Silicon Valley, a spin-off of the Institute for Automotive Engineering at RWTH Aachen University in Germany. SimLab allows new algorithms and schemes to be included in the control loop, and therefore, different technology developers can test their solutions before production. Another joint effort is the collaboration between the Center for Automotive Research at Stanford (CARS) and Toyota Collaborative Safety Research Center (CSRC Toyota). This collaboration has designed an interactive simulator that simulates not only vehicular dynamics, but also couples it with driver behavior and monitors human brain activities through interfaces.[20]

veDYNA[21] is another real-time simulation tool for autonomous vehicles. veDYNA lets individual consumers and/or corporations carry out comprehensive tests that range from conceptual autonomous car development to functional-level testing of the whole vehicle. veDYNA comes with comprehensive flavors that can meet both the individual user's and corporate needs. Based on the requirements, veDYNA offers standard, light, and entry-level functionality. Each product level contains features such as MATLAB support, whereas Simulink support is only available for the light and standard versions. veDYNA also supports various vehicle models that meet major test requirements for autonomous car dynamics.

The Aimsun simulator[22] is a hybrid simulator that combines the characteristics of macroscopic and microscopic simulation with mesoscopic simulation; this increases the granularity of the simulation environment [131], [132]. Mescoscopic simulation model simulates the traffic dynamics in the form of small groups rather than individual elements/nodes (microscopic) or high-level representation of the whole network (macroscopic). In other words, mesoscopic models fall between microscopic and macroscopic models. An example of a mesoscopic model is platooning in vehicular networks, where a group of vehicles are traveling together; this is taken into account and simulated for the required behavior. Aimsun is a commercial software solution for traffic simulations. This combination enables testing for many traffic scenarios on available road networks. Aimsun also provides users with the choice of stochastic route selection and the generation of subnetworks within the network. Simulation speed is another distinguishing feature of Aimsun, because of its multithreaded software architecture. Aimsun is used mainly for operational traffic modeling that enables the modeling of any network size (from a single lane to an entire region). In addition to other features such as user friendliness, hybrid simulation (microscopic, macroscopic, and mesoscopic), fast execution with multithreaded software architecture, openness and integration with other software, and multiplatform architecture, Aimsun provides users, government agencies, researchers, consultants, and corporations with additional features such as safety analysis, and evaluation of policies for intelligent transportation systems and autonomous driving.

Table IV presents a summary of the simulation tools that are currently available for simulation testing of autonomous cars. The simulation tools listed in Table IV are either open-source or proprietary. The proprietary simulators usually have more optimized functionality but come with subscription or purchase cost whereas the open source tools can be optimized according to the scenarios to be simulated. Furthermore, with open-source tools, the community of developers is available for support when needed. Nevertheless, the choice of a simulation tool depends on the needs and the budget. Among the simulator tools mentioned, SUMO, NS2, and NS3, and OMNET++ are the most popular simulation tools used by the academic community working on smart cars, connected vehicles, and vehicular networks because of their ease-of-use and functionalities [8]. However, these tools simulate only few aspects of the autonomous car and do not support the simulation environment required for autonomous car in a holistic way. Table III presents a summary of the design and implementation challenges for autonomous cars.

VI. Autonomous Cars' Challenges for Deployment

In this section, we discuss some of the current and future challenges that must be addressed by various stakeholders (automobile manufacturers, academia, software developers, policymakers, hardware engineers, and others) in the future to enable the ubiquitous deployment and full commercialization of autonomous cars. We classify the challenges into several categories: namely, technical, non-technical, social, and policy.

Fig. 4 presents the detailed taxonomy of future deployment challenges for autonomous cars and we summarize the deployment challenges in Table V.

A. Technical Challenges

In this section, we discuss autonomous cars' technical challenges. These challenges include validation and testing,

[18] http://moralmachine.mit.edu/
[19] http://www.fka.de/fka-sv/fka-sv-e.php
[20] http://revs.stanford.edu/
[21] https://www.tesis-dynaware.com/en/products/vedyna/overview.html
[22] https://www.aimsun.com/aimsun/top-features/

TABLE III
SUMMARY OF DESIGN AND IMPLEMENTATION CHALLENGES FOR AUTONOMOUS CARS

Aspect	Challenge	Implications	Possible solutions
Cost	• Hardware cost • Software cost • Management cost	• Reduction in car ownership • Adverse effect on business and auto industry	• Mass production will relax this issue
Maps	• Real-time map generation takes enormous computing resources • Storage overhead • Extreme weather conditions • Changing environment and road structures	• Poor mapping may jeopardize the functionality and maneuvers of autonomous cars • Need for more resources	• Big data solutions • Cooperative mapping through neighbors
Software Complexity	• Testing and validation • Requirements are not complete • Environmental complexity causes software instability • Software cost • Software security • Right-of-way provisions through software are difficult	• Delay in commercialization • Consumer trust is an issue • Investment risk to investors	• Driving profiles and fail-safeness • Focus more on AI and deep learning-based solutions
Simulation	• No universal simulator • Different simulators for different modules • Proprietary tools • Difficult to test all the requirements	• Incomplete testing and validation • Economic alternative for autonomous car testing • Validation of simulation results is hard	• Focus on open source tools • Make the data available for testing • A holistic approach is essential

trust, software quality, computational resources, safety and reliability, and privacy and security.

1) Validation and Testing: Validation and testing are two of the most important phases of system development. Depending on the degree of sophistication, the time and efforts required for validation and testing vary. There are several techniques for validation and testing, ranging from a simple bug hunt to a full-scale quality testing. However, mission-critical and safety-critical systems require fine-tuned exhaustive validation and testing to make sure that all the stringent requirements are met. An autonomous car is a safety-critical and complex system because any decision made by the system software will directly affect human lives. Koopman *et al.* carried out a comprehensive overview of the testing and validation challenges for autonomous cars [133]. According to this study, the system V model, if applied correctly, could achieve promising results through three approaches: phased deployment, monitor/actuator architecture, and fault injection (we will describe more on the system V model momentarily). Phased deployment refers to the fact that autonomous car cannot be built as one unit, it has to be incremental. The monitor/actuator architecture, on the other hand, will help with requirements complexity and enable fail-safe mechanism in autonomous vehicles. The third approach is fault injection, which can help in autonomous vehicles' validation process. Here, we discuss some of the main issues concerning testing and validation of autonomous cars that have impeded their rate of deployment.

The International Standardization Organization (ISO) has defined a standard for the functional safety of electrical and/or electronic systems in automobiles (ISO 26262,)[23] which defines the functional safety features of a generic automobile in production. This standard could serve as an abstract template for the complex autonomous systems. However, it does not cover the wide range of different possible scenarios and test cases that an autonomous car will be subject to. The ISO 26262 standard mandates a particular development framework referred to as the V model (as shown in Fig. 5).

The V model of testing and validation has been used in the automotive industry for a long time and has become the de facto ISO 26262 standard. Fig. 5 shows that the model V is composed of subsystems, and each one is validated and tested independently. For the generic automotive system, model V works well because the specific requirements of general automotive vehicles are well-defined and cover all the system's expected functionalities. However, autonomous cars have unique challenges and a complex set of requirements. In particular, the autonomous car's unique feature is that there is no driver, and this affects the traditional validation and testing techniques for autonomous cars. When a driver is behind the wheel, no matter how complex the situation is, the human mind can still think of, at least in most of the circumstances, better alternative or guarantee fail-safeness. In contrast, with autonomous cars, there is a higher degree of uncertainty of the scenarios and the system's response to it. Such circumstances may include simple scenarios such as, but not limited to, bad weather, fog, traffic lights violation by other cars, pedestrians, and more complex driving rules or conditions at intersections and traffic lights. The bottom line is that a complete set of requirements is not feasible and possible for the autonomous car. Therefore, an alternative is needed. To this end, Koopman *et al.* suggested that the complex requirements challenges, at least in part, could be reduced by limiting the autonomous car's operational concepts [133]. This would

[23]http://www.iso.org/iso/catalogue_detail?csnumber=43464

TABLE IV
COMPARISON OF DIFFERENT TRAFFIC SIMULATORS

Simulator	Language	Scope	Mobility Model	Features	Distribution	Architecture	Developer	Platform
Simulink	MATLAB	In-Car environment	In-Car	CAN and XCP communication, sensor fusion, driver models	Commercial	Ubiquitous, API-based	MathWorks	Windows, Unix, Mac
MATSim	Java-based framework	QSim and JDEQSim	Macroscopic, Microscopic	Large Scenarios Private and Public Traffic Fast Dynamic Agent-Based Traffic Simulation Modular Approach	Open source	Multi-agent	ETH Zurich and partners	Windows
TRANSIMS	Python-based run-time environment	Transportation and individual travel behavior	Macroscopic,	Simulates very large networks and for a long time	Open source	Cellular automata, Agent, Graph-based	NDSSL, USDoT	Windows, Linux
SUMO	C/C++	Vehicle-Vehicle, Vehicle-Anything communication	Microscopic	Simulation of multimodal traffic,	Open source	Command line and GUI-based environment	Institute of Transportation Systems Berlin	Windows, Linux
Vissim	Vissim COM Matlab	planning of urban and extra-urban transport infrastructure	Microscopic, Mesoscopic	Visualization in 2D and 3D Virtual testing of autonomous vehicles	Commercial	Multimodal traffic flow	PTV Planung Transport Verkehr AG, Germany	Windows
SimLab	N/A	Car mechanical dynamics	N/A	Simulates different user-defined simulation models Virtual Test Drive	Commercial	N/A	fka Germany	N/A
veDyna	Matlab	Car mechanical dynamics	N/A	Component development and testing 3D road model 3D-Animation	Commercial	Modular, Integration with other user-defined modules	TESIS DYNAware	Windows
AimSun	Python scripting	Large transport networks (cities)	Microscopic, Mesoscopic	Multi-platform, Fast execution, extensible and extensible	Commercial	Multi-threaded Simulation architecture Systems	Transport Linux, Mac	Windows,
CarSim	Matlab, Simulink, C++	Car mechanical dynamics	Mechanical, Microscopic	Vehicle dynamics analysis	Commercial	Standalone application	Mechanical Simulations	Windows, Linux

CAN: Controller area network
JDEQSim: Java Discrete Event Queue Simulation
NDSSL: Network Dynamics and Simulation Science Laboratory

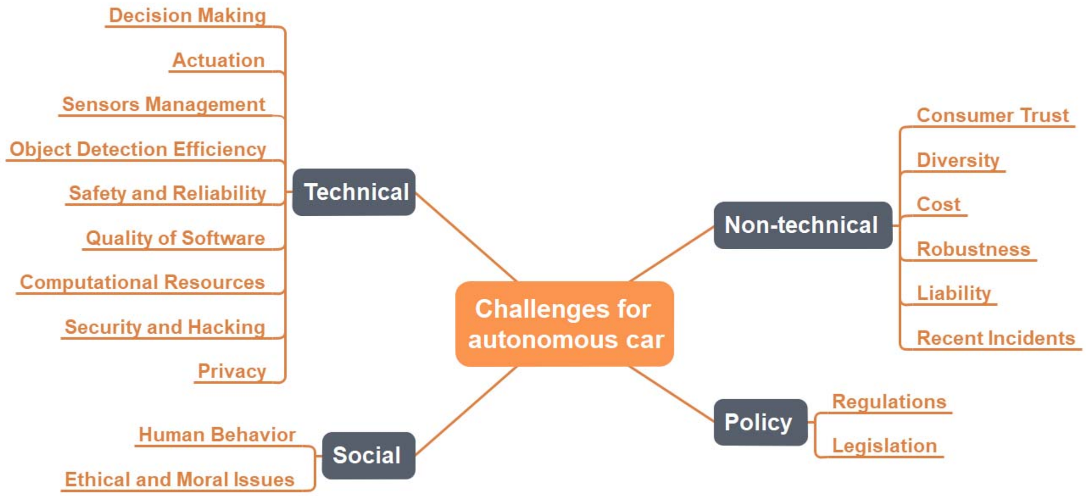

Fig. 4. Current and future challenges for autonomous cars.

indeed reduce the combinatorial explosion of the requirements complexity, which would limit the full potential of the commercial autonomous car from being achieved. But limiting the operational concepts could serve as a bootstrap for the full-scale testing and validation of autonomous cars [134], [135]. It is also worth noting that mission-critical and/or safety-critical systems require more extensive testing due to their interdependence on numerous domains other than the primary application itself [136], [137]. Therefore, it is well-understood that current testing strategies for autonomous cars, although extensive and concrete, cannot cover the full spectrum of safety and functional requirements, and the uncertain behavior exhibited by autonomous cars [98], [138], [139].

To address the aforementioned complex requirements, subsystems in autonomous cars can be abstractly divided into safety and non-safety-related subsystems, whereas in the bootstrapping phase, only strict safety-related systems are considered for full-scale testing [140]. The main challenge with this approach is the high unpredictability caused by the environment, human, hardware, and software factors that make this approach less effective.

Moreover, an autonomous car's operation is not strictly static and therefore deterministic approaches will not be efficient. Autonomous cars use a comprehensive and sophisticated decision-support system that needs concrete knowledge of the context and situation awareness. Therefore, inductive referencing and machine learning techniques and algorithms are likely to be more effective in autonomous cars. These approaches require a fine-tuned calibration of the sensors, actuators, and other units that provide data to the central decision-support system of the autonomous car [133], [141]–[143]. Machine learning itself brings about other challenges to the already challenging testing and validation process of autonomous cars. At its core, machine learning employs many techniques, such as active learning, inductive learning, supervised learning, semi-supervised learning, unsupervised learning, deep learning, and so on [144]. To understand the level of complexity, consider both images and videos taken/recorded through monocular means of the autonomous car to detect certain objects and/or patterns such as pedestrians, other cars, and humans. For this purpose, the classifiers for the machine learning algorithms must be trained on sufficient data to detect objects with high certainty [139]. These aforementioned learning and training issues make the validation of algorithms and software for autonomous cars during the training phase more challenging. But the new and improved behavior of the autonomous car system in the production phase will be different from what was observed during the testing phase [145]. This evolutionary nature of the dynamic behavior and learning-based approach for the autonomous car system also poses new challenges for safety validation and certification. To date, validation tools such as formal methods are inadequate for the autonomous car environment. Therefore, Kianfar *et al.* [146] and Koopman and Wagner [147] argued for novel methods for safety validation for the autonomous car system.

Finally, fail-safe and fail-stop approaches have been effective for decades in mission-critical systems in the aeronautical field. However, many of these systems use redundancy so that in case of a failure, the redundant module can replace the faulty one. This approach reduces the chances of complete and unsafe failure at the expense of extra cost and other resources. According to the literature, fail-operation systems require 3 redundant modules, whereas Byzantine fault-tolerant systems require 4 redundant modules [148]. In the case of an airplane, such redundancy helps because of stringent aviation rules and safety concerns. However, for the car industry this would be excessive from a consumer's point of view. It will not only increase the cost of the car but also introduce additional hardware and software complexity. The fail-safe approach in autonomous cars refer to degradation and/or the decrease in functionalities of the autonomous car. In other words, in case of any kind of failure in the autonomous car system (based on the type of failure), the fail-safe module will be triggered to minimize the damage that could otherwise be serious, for instance failure of the communication module could endanger the autonomous car's whole operation and the car could either

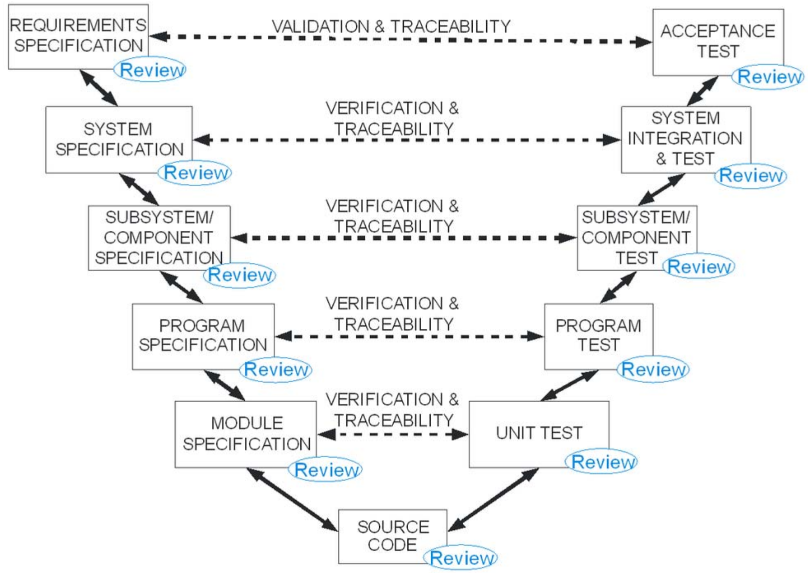

Fig. 5. ISO26262 Model V testing and validation architecture.[24]

move very slowly on the road or stop. On the other hand, the fail-stop mechanism refers to the fact that in case of a failure, the component that the caused failure stops operating and the component is identified. Depending on the type of component, the operation of the autonomous car is then decided. Fail-safe approaches work more efficiently and effectively in autonomous cars than in airplanes. In the autonomous car, to achieve fail-safeness, the car can quickly pull over to avoid any damages. In contrast, an airplane could take hours to land at the nearest airport. Fail-safeness easily can be achieved more effectively in autonomous cars if there is a slight compromise on the length of the operational duration [147]. When the operational durations are short, the system can trigger the fail-safe option when a system or any other failure occurs.

So far, we have outlined the traditional testing techniques for complex software validation. Wagner at and Koopman [149] argued that non-traditional approaches such as falsification are better for validating complex software systems, such as those found in autonomous cars. This type of validation and verification theory is based on the theories of Karl Popper, who advocated for science to be an adversarial process of falsifying existing theories instead of a constructive process of building theories [150]. In other words, this theory is related to the famous concept of "denying the consequent" (also referred to as *Modus Tollens*). This method of verification can be quite useful because of its space and process efficiency. In the falsification method, a single counterexample is enough to falsify a theory, and Popper inferred that for a theory to be meaningful, it must be falsifiable. This way, the testers do not have to go through the hectic process of collecting verification data and derive proofs. It is worth noting that the method of falsification helps in articulating complex requirements for cases where they are often ambiguous. Furthermore, this method also helps in software testing and verification where the existence of the counterexamples enable testers and developers of the software to detect and remove software bugs. Therefore, such a method could be useful for testing and validating software systems for autonomous cars. In other words, through the aforementioned theory of falsification, the autonomous car software testers look for negative test results that will also help in the reiteration and improvement of the software.

To summarize the validation and testing challenges of autonomous cars, we found that a definitive solution has not yet been developed, at least during the first stage of autonomous car development. Fault injection is considered to be one of the successful mechanisms to evaluate the robustness and performance of complex systems [151]. Fault injection works by introducing faults to the testing environment and it is used to attempt the falsification of safety claims, which indirectly helps to improve safety. Koopman and Wagner believe that fault injection will outperform current techniques, such as traditional testing and validation and model V testing that are used in autonomous cars' performance analysis [133]. It is worth pointing out that fault injection-based techniques have already been used in autonomous car development [152], but this has not quite matured yet. Furthermore, risk assessment is also another important factor in autonomous car and has been considered by Dominic *et al.* [153]. The authors proposed a reference framework that describes new attack surfaces for the autonomous cars. This architecture considers existing threats to develop a customizable threat model that can assess the risks of current and new threats to autonomous cars.

2) Safety and Reliability: A critical issue to address for autonomous cars is their safety and reliability. We may argue that autonomous cars must conduct test drives equal to hundreds of millions of miles before this technology is commercialized. In general, to some extent, non-critical statistical analysis may help in determining the degree of reliability of a system, but the amount of data required to perform such analysis is huge. In the case of autonomous cars, such data is the distance traveled by the car. Based on this assumption, the amount of time required for the autonomous car technology to

[24]http://users.ece.cmu.edu/~koopman/lectures/ece649/03_requirements.pdf

TABLE V
RESEARCH AND DEPLOYMENT CHALLENGES IN AUTONOMOUS CARS

Class	Key challenges	Possible solutions
T: Technical Challenges NT: Non-technical Challenges S: Social challenges P: Policy challenges		
T1: Validation/ Testing	• No complete set of requirements • Dynamic and non-deterministic operations • Complexity of operations • Mission-critical nature	• Functional division of software/hardware components • Limited operational concepts • Inductive referencing and machine learning methods • Fault injection
T2: Safety and reliability	• Distance driven in test drives does not determine reliability • Resemblance to human-level confidence in reliability needs a lot of resources • Legislation is vague • Removal of disengagement function is risky • Unclear validation cycle	• Defining short-term safe missions • Defining more fail-safe systems • Developing sophisticated algorithms for small missions • Employing ML, DL, and AI
T3: Software quality	• Huge budget requirements • Too many unforeseen scenarios • Autonomous car and its software represent complex system	• Fail-safe rather than unpredictable outcomes • Degradation of functionality when needed • Goal-oriented software quality testing
T4: Computational resources	• Autonomous car is host to heterogeneous sensors • Massive amounts of data produced • Increase in cost • Real-time data processing • Redundancy increases reliability as well as costs	• Graphics Processing Units (GPUs) • Optimized system on chip • Agreement on standards to make it more open to research
T5: Security and hacking threats	• Autonomous car operates in networked environment and is prone to network attacks • CAN bus (in)security • Malicious code injection, jamming, fuzzing, and hacking threats • DDoS attacks	• Separate data security from communication security • Efficient and effective authentication • AI-based security approaches • Security by design
T6: Privacy	• Who stores the data? • Sharing personal and location data has privacy implications • Convincing consumers to share personal data • Conflict between privacy and quality of service	• Consumer awareness • General Data Protection Regulation (GDPR)[25] • Acceptable trade-off between anonymity and quality of information

(Continued)

drive its way to safety, is tens and sometimes even hundreds of years [154]. An autonomous car must drive itself around 291 million miles without fatality to guarantee 95% confidence in resemblance to a human driver. This is a giant test drive for a driverless car [155]. Even if the confidence level is relaxed to 50% instead of 95%, autonomous cars still must

[25]https://www.eugdpr.org/

TABLE V
CONTINUED

Class	Key Challenges	Possible Solutions
T7: Accuracy and efficiency of object detection	• Trajectory is not constant • Real-time object detection is hard • Limitations of RADAR and LIDAR • Calibration of detection components	• Use of finite-state machine for incremental path planning • Intelligent role-based and contextual cooperative mechanisms among components
T8: Sensors management	• Data from many sensors must be processed in real-time • Deep learning algorithms are storage and compute intensive • Data redundancy, outliers, and granularity from sensors data • Authenticity of sensed data	• Increasing computation and communication resources • Crowd-sourcing and crowd-sensing • Sharing sensors' data across nodes • Trade-off between number of sensors and efficiency of data processing
T9: Decision making procedures	• Unpredictable environment • Human behavior is difficult to realize through a machine • Optimal decisions are challenging to make • Difficult to detect fault and malfunctions of the system	• Context-aware object detection and perception • Situation-awareness • Context- and situation-aware decision and control algorithms
T10: Actuation	• Adaptation to unknown environment • Actuator saturation • Wrong input can lead to severe consequences	• Fuzzy and Takagi-Sugeno model for actuation • Input validation for actuators
NT1: Consumer trust	• Consumers may be reluctant to trust autonomous cars • Testing does not answer all the questions/concerns of consumers • Lack of universal adequate legislation • Security and consumers' privacy • Difficult to mimic human driving behavior	• US-led legislation initiative for autonomous car • Startups aiming at increasing consumer trust • Promoting awareness and incentives • Promotion of success stories • Guarantee of fail-safeness • Limit the number of functionalities
NT2: Diversity	• Coping with connected and non-connected vehicles • Human factor in driving is essential • Uncertainty in human driving • Unpredictable behavior of autonomous car towards human drivers • Environmental diversity	• Implementation of stringent traffic laws • Detection and isolation of malicious driving behaviors • Social training
NT3: Uncertain cost	• Software cost is too high • Maintenance and testing are expensive • Hardware is too expensive at the moment • Service subscription, enhanced maps updates, and other costs • Return on investment for service providers	• Limited functionalities • Leveled utilities and costs • Use of autonomous car as a utility • Cost-effective business model • Focus on consumer satisfaction

(Continued)

TABLE V
CONTINUED

Class	Key Challenges	Possible Solutions
NT4: Operational robustness	• Real-time decision in unpredictable scenarios • Crowd management • Hostile environments	• Fail-safeness • Driving profiles • Object recognition in real-time • Learning from surroundings • Intelligent traffic lights management
NT5: Liabilities	• Who will be responsible for accident? • Who will be insured? Car owner, occupant, or manufacturer? • Manufacturer might put hidden purchase costs to make-up for their liability losses	• New business model and new regulations/legislations • Rethinking of insurance business • Manufacturer-centric solutions • Efficient forensic solutions
NT6: Recent incidents	• Recent real-life autonomous car accidents decreased consumer confidence • Humans do not tend to trust machines with their lives • All unforeseen scenarios are not possible to cover	• Rethink the race for being first in commercialization of autonomous cars • Fail-safeness • Minimize the damage • Open-source software development
S1: Human behavior	• Humans are generally reluctant to change their behaviors • Drivers' behaviors towards autonomous car can be aggressive • Autonomous car may not fully mimic human driving and thinking behavior	• Educate people about the technology • Service providers should provide training/tutorials to the public
S2: Ethical and moral consequences	• *Right-of-way* is more complicated in case of autonomous car • Human empathy cannot be implemented in autonomous car • Trolley problem • Hard to make optimal decisions • Social equity concerns	• Fast intelligent and real-time response with efficient software will mitigate such cases • Implement multiple ethical theories and test • Implement different driving behaviors • Alternate jobs for people who will lose their jobs
P1: Policy challenges	• Re-examine many policies may open up further policy challenges • No clear policy since autonomous cars are not commercialized yet • Safety and utility are inversely proportional • No clear policy for autonomous car certification	• Policies are already being implemented • Recommendations that encompass the concerns of all the stakeholders • International task force comprised of all stakeholders to develop sound policies

travel 67 million miles without fatality. This critical requirement impedes the success of this emerging technology. These reports, and the fact that safety must be the primary concern for driverless cars, require new methods of measuring the reliability of autonomous cars.

Legislation is another challenge for autonomous car technology (at least at the moment). According to California state law, during the test drives of automated cars, a human driver must be present behind the wheel to take control in case of any system failure or any other malfunction that jeopardizes the safety of the driver, other cars, and pedestrians. This requirement clearly violates the essence of Level 4 and Level 5[26] [156] that the automated car must be capable of operating itself without human intervention, even during the testing phase. Safety and reliability of the automated car is still in its infancy and it will take time to meet the safety and reliability standards. A more in-depth discussion of the challenges and features of autonomous cars' safety can be found in the survey conducted by Koopman and Wagner [147]. The safety of the automated car system is an interdisciplinary issue, and therefore a large portion of the autonomous car's development lifecycle is likely to be spent on safety certification [157].

To achieve an acceptable degree of reliability, one solution could be to define a short-term safe mission time for an autonomous car [147]. Such a safe mission could be a few seconds instead of minutes and hours in case of a critical failure. The fact that vehicles can perform a safe mission in seconds (for instance pulling over to the roadside) gives them an edge over other complex systems such as airplanes. Therefore, such a safe mission could be triggered in case of any serious component failure and thereby increase the reliability. In this case, if a failure occurs, the fail-safe system could intervene (for instance, to reduce speed, change lanes, and stop the car) and avoid potential damages [147]. In contrast, in automated cars, such fail-safeness could be more effective because a human driver can take control in unwanted circumstances and drive the car manually. The designers of the autonomous car system have the choice to define short-term missions for the autonomous car and relax some of the complex requirements for it. In 2016, a Google driverless car underwent only 124 'interventions' while testing on the road [158]. Of those 124 disengagements, 8% were caused by the reckless behavior of other drivers on the road, whereas the rest were caused by software issues and unwanted behavior from the vehicle. Although the results are promising as compared to previous years, such results demonstrate that we are still far from achieving full disengagement. The test results also showed that automated cars are not yet mature enough to handle the full spectrum of unforeseen circumstances on the road.

To guarantee safety and reliability in autonomous cars, there is still much research work that must be undertaken prior to their commercial deployment. As we mentioned previously, safety and reliability are multidimensional aspects of the autonomous car. Therefore, more research is needed to examine the test and validation cycle of autonomous cars before rolling them out on the market. To summarize, the main factors that play a fundamental role in the reliability and safety of the autonomous car include flexible, intelligent, efficient, and secure software systems with high-end sophisticated algorithms, artificial intelligence support, and a highly efficient decision-support system. Although extensive research has already been undertaken in most of these areas, nonetheless, the unique set of requirements of the autonomous car calls for more fine tuning and accuracy in these areas. The reason is straightforward: if the autonomous car is not reliable and safe, this technology is doomed to fail.

[26]https://www.nhtsa.gov/

3) Software Quality: At the very basic level, the autonomous car is operated by complex and sophisticated software. The degree of complexity that goes into the software of the autonomous car must be able to mimic the human brain and/or behavior. The seriousness of a situation can be, at least in part, compared with airplane manufacturers that build a safe or at least fail-safe software for the airplane, although airplanes are still somehow operated by human pilots. Furthermore, a major portion of software development budget is spent on testing and validation. In mission-critical and complex systems such as airplanes and autonomous cars, testing and validation is even more important, because it directly affects human lives. This demonstrates the critical importance and role of mission-critical software used in these systems. Besides, in autonomous cars, the driver is absent, which means we need even more stringent methods to ensure the highest software quality. It is true that vehicular movement is restricted by the road topology, but even within these restrictions, vehicles have many possibilities to maneuver, making it quite a complex system. In order for the autonomous car to function reliably, its system software should be able to handle most unforeseen events in a safe manner. Therefore, it is important for autonomous car software designers to make sure that the software responds to a wide range of unforeseen scenarios. The most important feature must be fail-safeness. During an uncertain event where the outcome of the possible maneuver jeopardizes occupants' safety, the system software should try to minimize the damage. The best action for the autonomous car in such a scenario could be the degradation of functionality to the safest level, which in some cases could be stopping the car altogether. Unless and until the autonomous car technology is mature enough, system designers should focus on fail-safeness rather than choosing an uncertain outcome. Such situations would, at least during the pilot stages of the autonomous car deployment, provide valuable feedback to the designers and will identify potential vulnerabilities and deficiencies.

4) Computational Resources: Today's high-end cars come with a fair amount of computation and storage capacity. The autonomous car is equipped with several high-resolution cameras to enable accurate vision and monitoring. Current luxury cars have between 7-9 imaging sensors for object recognition, while autonomous cars typically have three classes of sensors: cameras, LIDAR, and radar [159]. The autonomous car requires more high-resolution images (and video) from cameras for more accurate driving behavior implementation, optimization, and so forth. The autonomous car will need more general-purpose and special-purpose processors, GPUs, an FPGA, and a system on a chip (SoC) to support its functional and operational needs. Another challenge for the autonomous car's computation system is the various computation-greedy subsystems such as LIDAR, geopositioning, radar, infotainment, and image processing. Traditionally, embedded computational resources such as GPUs are kept near the sensors as much as possible to decrease the possibility of signal loss, degradation, and interference. However, such an approach requires more processors and a more complex networked system for autonomous cars. Furthermore, the system architecture and design for autonomous and connected cars, currently being heavily discussed in the research community, needs to be able to handle issues such as a dashboard design, geometry, and space distribution for the hardware [84], [160]–[162]. To date, no clearly defined approach for the autonomous car's underlying system architecture is openly available from original equipment manufacturers (OEMs).

The high real-time data processing rate and use of sophisticated algorithms will increase the need for efficient, reliable, and cost-effective hardware for the autonomous car. Furthermore, any redundancy approach will increase costs further. It is also worth noting that for image processing and digital signal processing, GPUs have proved to be more efficient than general-purpose processors. Therefore, we can foresee that more research on embedded processors will be needed in the future to increase speed, reliability, and efficiency. The current hardware systems used in autonomous cars are usually proprietary, which make their scalability and interoperability difficult. If the auto makers and autonomous car designers agree on common standards and the type of hardware in their products, it would simplify the upgrade of existing technologies for autonomous car technology.

5) Security and Hacking Threats: Traditionally, security has been one of the most important issues of autonomous cars. The concept of autonomous car is one of the important components of intelligent transportation systems, and a lot of research has been undertaken recently on different aspects of connected cars that include applications, services, security, privacy, infotainment, and business models [1], [6], [163]–[169]. Security and privacy are major factors impeding the deployment of connected car technology, despite noteworthy research outcomes. In connected car technology, the data are shared among vehicles and with the infrastructure for various purposes, ranging from value-added services to safety applications. Therefore, it is important to ensure the quality of the data. Furthermore, the data must not be accessible to unauthorized entities. User and location information must be secure during all communications. A tremendous amount of research has already been conducted to mitigate different types of threats in the connected car environment [168], [170]–[175]. These existing threat mitigation techniques leverage both traditional cryptographic mechanisms and non-cryptographic mechanisms to provide security and privacy. The internal system architecture of the car is itself a complex network of different components including, but not limited to, sensors, actuators, handheld devices, and ECUs, all of which often connect through the CAN bus [176], [177]. The possibility of remote operations of a car for diagnostics and maintenance purposes poses risks to the overall security of the car as well. Although some solutions have already been proposed to address CAN bus-related security concerns [45], [178], [179], these solutions do not fully mitigate the risks involved with CAN bus technology used in current cars. Recently, it has been shown that connected cars can be successfully hacked through various methods by exploiting the CAN bus. Woo *et al.* demonstrated a practical wireless attack on a connected car through the CAN bus [44]. The attack leveraged a diagnostic channel of the connected car through a rogue android application, which circumvented the CAN bus's security mechanism. There are several other attacks that can be launched on high-end connected cars [30], [180].

At its core, the autonomous car hosts a network of sensors and other communication devices that provide data as input to the decision support system, which drives the autonomous car in a designated way. The security of these devices must be protected. The traditional security threats these devices can encounter include hacking into an in-car network, injection of malicious code into different sensors and into other units such as the telematics unit, external signal spoofing during communication, packet sniffing, packet fuzzing, jamming, and so on [181]–[184]. For instance, because the autonomous car uses both radar and LIDAR technologies, jammers would jeopardize the autonomous car's security and its occupants [185]. Furthermore, the data generated by different components of the car (such as radar, sensors, GPS, and other modules) are also used by auto manufacturers for diagnostic and maintenance operations, as well as by service providers to offer accurate and efficient location-based services [186], [187]. Information fusion based on data from various sources in connected cars and the autonomous car environment will have significant security challenges that must be resolved [188]. Anomaly detection, data quality, data integrity, and availability are of prime importance to harness the full functionalities of the automated car as well as connected cars. In the case of the latter, the data are not only generated locally, but can also be received from neighbor vehicles. For instance, the evolution of the Future Internet Architecture (FIA) opens up new opportunities in the content-centric networking paradigm. Content-centric networks [189] have been used for connected car technology to enable cars to share contents [190]–[192]. CarSpeak is a platform through which a car can request sensory information from a neighboring car [193]. This platform enables data sharing among vehicles on the road, but also requires stringent security measures to protect the shared data on a large scale.

The distinguishing characteristic between the connected car and the automated car is that the driver is always behind the wheel and ready to intervene if there is a need for a connected car. In contrast to the automated car, there is no driver to take control even if one or more systems of the automated car are compromised. Therefore, the automated car requires preventive measures in addition to the detection of unwanted events. The automated car will inherit all the inherent security issues that are associated with sensors, communication networks, and short-range communications. Therefore, security is going to be critical in the development of autonomous cars in the future. A fully automated system such as an autonomous car would be a favorite target for selfish users, hackers, disgruntled employees, or terrorist organizations. In worst cases, such vehicles could be used for terrorist activities without needing a driver behind the wheel. Furthermore, keeping in mind the degree of sophistication of current malware types, one such variant could quickly bring down the whole fleet of autonomous cars through distributed and coordinated attacks. Petit *et al.* conducted a thorough survey pertaining to cyberthreats in autonomous car systems [194]. The authors discussed possible cyberthreats and attack surfaces for both the standalone autonomous car and connected autonomous cars according to the SAE J3016_201609 standard [195].

Connected vehicle technology has considered secure development during every step of the process, starting from requirements specifications, design, and software development all the way to prior to its deployment. This could be a starting point for autonomous cars, too. For example, separating mission-critical and communication systems in complex systems such as autonomous cars might help mitigate cyberattacks or at least make it more difficult for the attackers. Artificial intelligence (AI)-based security mechanisms have also been adapted for connected cars [196]. The authors employed AI approaches to mitigate DoS attacks in connected cars by learning the behavior of the neighbors through the authenticity of the safety messages. Current solutions check the authenticity of every safety message which make them prone to DoS attack. When AI is used, it is not necessary to authenticate every message but to learn the behavior of messages. However, the enormous amount of data generated in the connected car environment is still a major issue and AI-based techniques are not yet mature enough to be used in autonomous cars [196].

It is well-known that security is usually considered to be an afterthought in most systems. However, it is one of the key components that must be considered at the design phase. From physical security to communication security, the autonomous car must be foolproof and tamper-resistant. To achieve these goals, more research is needed in security. Traditionally, security includes cryptographic primitives that consume a lot of resources and adversely affect performance. For the autonomous car, given that computation resources are expensive assets, security mechanisms that are in use must therefore be highly resource-efficient and at the same time maintain high performance. Further research insights are needed to identify real-world threats such as malware, communication and physical security, and covert communication in addition to the traditional existing security challenges for autonomous cars. It is also worth mentioning that connected vehicle technology has undergone a lot of research from both security and functional perspectives. More research is needed to investigate if the security research results for the connected car can be applied to the autonomous car as well.

6) Privacy: The idea of self-driving cars is appealing but equally alarming from security and privacy perspectives. In September 2014, a consumer advocacy organization in the United States warned that the legislation of the "robot car" in California does not guarantee user privacy. The data collected from autonomous cars contains personal data that may be shared intentionally or unintentionally with others, putting the user's privacy at stake. When it comes to privacy, the following five important questions should be answered with regard to consumer satisfaction [24] in mind.

1) Who should control the data?
2) What type of data must be stored?
3) With whom will the collected data be shared?
4) In what form will the data be available?
5) For how long will the data be stored?

Some of the aforementioned questions are quite easy to answer. For instance, in the case of accidents that will require investigation, post-crash data can be shared with insurance agencies and law enforcement agencies. In current transportation systems, government transportation agencies and/or other service providers collect traffic data from different sources such as traffic cameras, road sensors, and so on, whereas in the case of connected vehicles and autonomous cars the same data also will be collected from the vehicles and then used in traffic planning, management, and information dissemination. This data might contain personal information such as travel routes, time of travel, and location information that might seriously jeopardize users' privacy. Therefore, in the autonomous car paradigm, the sharing of such data might not be acceptable for consumers at the cost of their privacy. It is also worth noting that the data generated by an autonomous car is far more than a connected vehicle, and could reveal not only information such as location and time, but also behavioral data that contains traffic patterns, personal interests, or community formation information. At the same time, this data, if handled with care, could provide quality of service to consumers in terms of advanced traffic information systems, improving dynamic traffic lights, urban planning, and much more. One challenge that autonomous car designers might face is the consumers' lack of motivation to share the AC's data even when privacy is ensured. The issue of privacy in autonomous cars is more complex than in normal connected cars. Usually in connected cars, shared information is in the form of a Cooperative Awareness Message (CAM) along with other safety-related messages. On the other hand, for an autonomous vehicle, the shared data are not only related to the CAM but also data from in-vehicle sensors, actuators, and other in-car communication systems. Therefore, the autonomous car data is rich in features, and hence, more prone to privacy abuse. One possible solution could be the use of incentives. For instance, by sharing the data consumers could be offered certain rewards in addition to the privacy guarantee. In a nutshell, sharing of such data is a tradeoff between the quality of services received by consumers and the level of required privacy for consumers. These two factors should be well-considered when autonomous cars are deployed on a massive scale.

Privacy is a conflicting and complex requirement for service providers and the government to guarantee. Therefore, conditional privacy [197] is considered to be more practical. With conditional privacy, the identities are subject to revocation in case of an emergency event, with agreement from the competent authorities (such as judiciary, law enforcement, and insurance agencies). To this end, data obfuscation and aggregation mechanisms could be used to preserve user privacy, although the granularity of the information should be within the threshold for the underlying application. Furthermore, identity-less information dissemination schemes [198] have also been used in some research efforts and could be useful for preserving privacy with autonomous cars. In short, privacy-preservation mechanisms should be an acceptable tradeoff between the quality of information and level of anonymity required by users. Furthermore, preserving location privacy is more challenging than user privacy, because of the adverse effect it can have on location-based services. For location privacy, various privacy solutions exist, such as location-based encryption and obfuscation [174], [199]–[202] that could benefit the autonomous car environment. More research is needed to develop efficient, scalable, and privacy-preserving solutions that can protect location privacy for autonomous cars.

7) Accuracy and Efficiency of Object Detection in Autonomous Car: LIDAR is used for short-range object detection (through distance measurement) in autonomous cars. The coverage range is the main limitation of LIDAR which means that it is not suitable for long distances. From motion and trajectory planning perspectives, it is important for the control of autonomous car to execute the plan incrementally because the planned trajectory may be obstructed by unforeseen objects or unpredictable behavior of the neighbors on the road. Furthermore, it also suffers from reflectivity issues. In contrast, radar uses radio waves for measuring the distance from the target object. However, radars have their own limitations despite their advantage of long range as compared to LIDAR. The reflectivity issue is even worst in radar and it can only detect metallic objects such as vehicles on the road. Radar cannot detect other objects such as pedestrians. Therefore, only LIDAR and radar will not work on their own. To address the issue of dynamic and runtime motion planning, some researchers have used finite-state machines to generate sub-goals as a re-planning incremental strategy. However, cooperation among different components including LIDAR, radar, ultrasonic, infrared, GPS, and inertial position system is essential. Another drawback with LIDAR is its high cost although has been decreasing recently and current LIDARs are more efficient [203]. The limitations of radars have also been extensively investigated which have yielded significant results in the form of optimized radars for autonomous vehicles [204]. Infrared sensors and ultrasonic sensors are used for short-range and adequately contribute to the overall functionality of autonomous vehicle. However, intelligent calibration of each sensor and collaboration among the sensors are needed.

8) Sensor Management in Autonomous Car: Autonomous cars have many sensors that generate a huge amount of data in real time. This data is used by different components of the car to function properly. However, the volume of data generated by sensors is too much to be handled by the computation-intensive deep learning- and computer vision-based algorithms. Therefore, this data poses significant challenges to the efficiency of the autonomous car. Other challenges from sensors' data include redundancy, outliers, granularity, and so on. To this end, efficient, and real-time data management system is essential for the autonomous car. To date, existing pilot versions by different automotive companies and startup companies use as many sensors as they could to make sure that all the systems work properly. This is achieved by maximizing computation and communication resources together, to make sure that the system operates according to the specifications. Currently, efficiency is not the primary concern for autonomous cars. However, in addition to functionality, efficiency needs to be considered along with data processing in commercial autonomous cars. Current data processing algorithms in autonomous cars - to be more precise - incur high computation and communication overheads. Therefore, crowdsourcing and crowdsensing will play a pivotal role in the future autonomous cars. In other words, instead of having a large array of sensors, having an optimum number of sensors and sharing sensors data among the neighbors are likely to produce better results. This approach seems promising but the mobility of autonomous vehicles and their interactions with each other and with the environment will pose many other challenges (such as - short interconnection time and authenticity of data) that have to be addressed. Furthermore, trade-off solution to this problem can be a consensus among cost of these sensors, the number of sensors, and the overhead that they incur on the data processing systems, and decision-making systems.

9) Decision-Making Procedures: It is well-known that the autonomous car will adjust its behavior according to the surrounding environment. However, the unpredictability of the environment poses serious challenges to the designers and developers of the autonomous car system. As we mentioned earlier, an ideal autonomous car would mimic the actual human behavior which would enable it to decide for the best possible outcome in a particular scenario. Recent advances in artificial intelligence, machine and deep learning techniques have led to interesting research results that can be leveraged by autonomous car technologies. However, there are still many challenges that need to be addressed when it comes to making optimum, real-time decisions. For instance, it is still very challenging to detect faults and malfunctions of the various systems (such as sensors and actuators) of the autonomous car. Therefore, the decision-making procedure of the autonomous car (according to the data available) may be sound but may not be optimal at the time. To this end, context-awareness is needed at the object detection and perception levels. Object detection and perception are two of the primary components of the autonomous car used to model situation awareness around the autonomous car. Additionally, context is equally important as an input parameter for the decision-making module. Context-awareness for autonomous cars has been investigated by only few researchers in autonomous car [205] and in related fields such as vehicular networks [206]. Further research is needed on context-awareness for autonomous cars. Therefore, a holistic approach is still needed to calibrate the real environment, the context, and the perception of the environment by the autonomous car.

10) Actuation: Actuators are responsible for regulating the input to a device or component in order to have the correct output. These devices are electrically operated. For instance, the fuel injector is an actuator which regulates the fuel injection into the engine. Actuation is an essential part of the control where the actual action is taken by a particular component of an autonomous car. Since autonomous cars must adapt to unknown environments and road conditions (both physical roads and the neighborhood), actuation becomes even more critical especially in the case of actuator saturation. Actuator saturation refers to a phenomenon where the actuator does not receive the input within the limits (both minimum and maximum). Such cases may lead to unwanted results which might cause dire consequences in mission-critical systems such as the autonomous car. To date, some researchers have investigated solutions to address the problem of actuator saturations through fuzzy system and Takagi-Sugeno Model [207], [208] but further research is still needed to address the issue of actuator saturation.

B. Non-Technical Challenges

In this section, we outline some non-technical challenges faced by autonomous cars. In addition to technical challenges, non-technical challenges must also be addressed before autonomous cars are fully commercialized. Next, we discuss some of these non-technical challenges.

1) Consumer Trust: One of the many obstacles of autonomous car technology is the lack of trust from a consumer perspective. It is also true that the challenges faced by autonomous cars cannot be mitigated by mechanical interlocks and tried-and-true technologies due to their limitations [149]. Autonomous cars are poised to reduce traffic accidents that may occur due to inattentive drivers. However, an attentive human driver will have strong capabilities of driving safely in unforeseen environments as compared to a "machine." Therefore, consumers may seem reluctant to put their faith in a "machine" when deciding on circumstances where their lives are at stake. Historically, testing is used as a viable approach to measure the level of trust in a new technology. In the realm of driving, the testing approach takes into account driving safety, crash avoidance, and so on. However, testing alone cannot answer all the questions raised by the consumers such as software failure, bugs, and unusual behavior. Furthermore, there is a huge difference between the risks posed by human drivers and those arising from the software in the autonomous car environment. For instance, a human driver can become drowsy during a long drive, whereas software does not. On the other hand, complex software has its own traditional shortcomings such as code defects, and non-traditional shortcomings such as vulnerabilities and/or exploits. It was recently reported in [27] that despite great opportunities and services provided by autonomous cars, the consumers' level of trust is still not that high. People are still hesitant and do not feel fully comfortable in the autonomous car and it will take more time before trust in such cars reaches a maturity level [27]. This trust factor is also related to regulation and legal issues, which we discuss in the following subsections. However, it is worth mentioning that a real breakthrough in the process of autonomous car legislation took place in February 2016 when the U.S. NHTSA announced that Google's artificial intelligence system is deemed to be considered a driver [209]. Consumer trust is of paramount importance, and it could be used in the commercial production and subsequent proliferation of autonomous cars.

Recently, efforts have been made to increase the consumers' or occupants' trust in autonomous car technology. A New York city-based startup called Braiq[27] aims to improve consumer trust in autonomous cars through emotional intelligence. The project is based on the sensory data available from different sensors monitoring occupants. In its essence, human facial expressions are captured through camera sensors, and sophisticated artificial intelligence algorithms deduce whether the autonomous car's occupants get nervous during the course of different maneuvers such as acceleration and deceleration. Based on the observed human behavior, autonomous cars can adjust their maneuvers accordingly. This approach helps autonomous cars' occupants feel relaxed and ultimately increases their trust level.

To increase consumer trust in the autonomous car system, we need strong involvement from both governments and auto makers. Some useful steps to increase consumer trust and interest for adopting autonomous car technology include, but are not limited to, promoting awareness, success stories, clear instructions, and upgrading the road infrastructure (traffic signs and lights). More research is needed in developing intelligent, efficient, smart, and fail-safe algorithms and systems to minimize failures and achieve the highest level of safety. It will be acceptable for consumers if the system is reliably fail-safe with a lower number of functionalities rather than unreliable with a high number of functionalities and services. More research is needed on autonomous cars in areas such as formal requirements specifications, intelligent control mechanisms, and connected automated cars.

2) Diversity (Technology-Enabled and Non-Enabled Vehicles): Currently, the autonomous car can drive itself in restricted conditions such as on roads with clear lane marking, clear weather, more on highways than in urban localities, and controlled speed limits. Vehicular diversity is an important challenge for autonomous cars. In the real world, autonomous cars will have to drive shoulder-to-shoulder with both non-technological vehicles and connected vehicles.[28] Both connected and non-connected vehicles include the human factor, which differentiates them from autonomous cars. Human behavior adds a level of uncertainty to the driving pattern, because each person drives a car with his or her own unique style. How the autonomous car reacts to the driving and behavioral patterns of other vehicles (under the control of humans) on the road remains an open research challenge. Besides vehicle diversity, there are other kinds of diversities as well, such as environmental diversity, social diversity, and others. For instance, current autonomous cars (in the testing phase) struggle with inclement weather conditions such as heavy rain, fog, storms, and snow [210]. However, some autonomous car technology companies have tested their cars in rainy weather and at night [211]; therefore, this problem will likely be solved in the near future. Similarly, it is a challenge for the autonomous car to know when a traffic police officer is waving his or her hand, asking the autonomous car to pull over. A fairly sophisticated technology must be built into the car to recognize and subsequently act when such events occur. At the moment, the autonomous

[27]https://braiq.ai/

[28]By connected vehicle, we mean the vehicles equipped with an on-board unit and able to communicate with other vehicles and with the infrastructure. Non-connected vehicles, on the other hand, refer to the vehicles that do not have this built-in functionality.

car technology is not mature enough to operate in such diverse conditions. Therefore, further research is still needed to develop relevant solutions. Furthermore, governments and other regulatory bodies should work toward new legislation for traffic laws that can apply also to autonomous cars. For instance, malicious human drivers could try to disrupt the normal autonomous car functions through aggressive and offensive driving behaviors. Such actions towards new technology could be reduced through strict traffic laws.

3) Uncertain Costs: It is speculated that the initial deployment of autonomous cars will incur a staggering cost due to expensive hardware and software [212]. As we mentioned in previous sections, the complex system's software costs may reach up to 50% of the system's total costs. Furthermore, to ensure the safety, reliability, and robustness of mission-critical components and sophisticated, high-end hardware, the cost will be several-fold compared to the normal vehicles. Autonomous driving, with all of the existing and non-existent challenges, provides noteworthy benefits to consumers, although at the expense of a higher price. Additionally, autonomous cars may require an additional expense in the form of annual service subscription, enhanced maps, software updates, liability, and so on. Therefore, it is still unclear whether the consumer will opt for autonomous car technology over existing vehicles and whether the benefits to be reaped are worth the higher costs. From a manufacturer's point of view, recovery of the cost of development, profit, and service fees will also increase the autonomous car's purchase value. A report by the Victoria Transport Policy Institute shows that the additional annual cost incurred by autonomous cars will range from U.S.$1,000 to $3000 [19]. We note that the projected actual cost incurred by the autonomous car is still a speculation and will be clearer in the years to come.

As autonomous car technology is still in the early stage of deployment, it will probably be unaffordable for some time to most consumers. One economical option would be the use of autonomous cars for the daily commute. In other words, using the autonomous car as a utility would be much more economical than owning a car. Therefore, car manufacturers and service providers should develop new and cost-effective business models that will earn them revenue, and enable people to use this technology in an affordable way.

4) Operational Robustness: The autonomous car will achieve most of the expected results in terms of functionality, operation, and other targeted features. However, timely decisions in some driving scenarios will still pose a serious challenge to designers of the intelligent autonomous car. One such scenarios is crowd management. In developed countries, traffic lights usually work in a highly systematic way, and thus the autonomous car can decide when to stop and when to move even in the absence of traffic lights. The situation is completely different in developing countries, so adaptation of autonomous cars in such an environment will be a real challenge. In large, crowded, and overpopulated cities such as Mumbai and Dhaka, even if the signal is green and the cars are good to go, people still cross the road. In this case, the autonomous car might have to wait forever or run over pedestrians. Therefore, testing the autonomous car for robustness and accuracy in such hostile conditions is imperative before deployment.

In light of these aforementioned scenarios, beyond taking into account traffic lights in the urban environment, the autonomous car also must be equipped with a highly efficient mechanism for recognizing objects in real time without delays. Careful driving profiles could also help autonomous cars avoid accidents. However, these issues are indirectly related to autonomous cars' behavioral aspects. Ideally, autonomous cars must learn behaviors from the surroundings and adapt their driving profiles accordingly. For instance, in crowded cities, the driving profile could be "cautious". Furthermore, dynamic traffic lights might help (to some extent) in eliminating problems (such as long delays at traffic lights and recognizing different objects) with traditional lights (e.g., during rush hours). Such upgraded traffic light systems will not only benefit autonomous cars but also connected car technology.

5) Liabilities: During unforeseen circumstances (such as accidents) while driving, forensics are of paramount importance for both insurance and law enforcement agencies. The current model (where we have a human driver behind the wheel) is, by far, efficient and acceptable to all parties (vehicle owners, insurance agencies, and law enforcement agencies). However, the autonomous car brings a completely new scenario for all the stakeholders. If an autonomous car is involved in an accident (e.g., the autonomous car runs over people or bumps into other vehicles), it will be challenging to justify the situation to insurance agencies and law enforcement agencies. In such cases, will the vehicle's owner (rather than the occupants) face charges regarding the accident? Or should the car manufacturer be the one ultimately responsible for it? There are many unresolved issues that need to be addressed for such scenarios in the future.

Recently, Volvo stated that they will take full responsibility for accidents caused by their autonomous cars [213]. At least for now, this does address some of the issues we raise regarding liability issues with autonomous cars. However, it is quite likely that car manufacturers will have to rethink their business model in such circumstances. To cope with their business and ensure profit revenues, we foresee that the car manufacturers will include hidden purchase costs for their products that will ultimately put more of a financial burden on consumers. Furthermore, we may also see a decline in the involvement of the insurance agencies if they are not involved with the claims (if these are being dealt with directly by car manufacturers). Another point of view is that, with the deployment of autonomous cars, insurance companies will have to rethink their business models, and the relationship between insurance companies and car owners may come to an end. In case of an accident, the insurance companies will insure the car manufacturers directly instead of the car owners [214].

These insurance and liability issues with autonomous cars will require concrete and serious legislation, where all stakeholders have a share in the responsibility. Concrete policies are also needed from the government for the insurance of both the autonomous car and its occupants. Traditional insurance plans might not work with autonomous cars. Although post-incident forensics might reveal the culprit(s) of an accident, outstanding issues (such as who to insure and how to insure) require insurance agencies to develop new business models for the autonomous car market.

6) Recent Incidents Involving Autonomous Cars: Another major challenge we need to address before deploying autonomous cars involves recent incidents caused by autonomous cars. In 2016, a Tesla Model S car crashed and killed a person in the self-driving mode. The accident took place when a tractor-trailer took a left turn in front of the Tesla car, and the self-driving car failed to apply the brakes. This was the first fatal accident caused by autonomous car technology. After that fatal crash, Tesla admitted the limitations of the currently available technology in their cars. No matter how much effort auto makers put into their products, there are so many unforeseen scenarios to anticipate. This fatal crash had a significant impact on consumer satisfaction and serious afterthoughts about the deployment of such technology, despite its numerous benefits. In addition to this accident, there have been a series of other incidents with automated cars. In 2016, a Google driverless car collided with another commercial van on the road. According to the reports [17], the accident was caused by confusion with traffic signals. In another accident, a Google driverless car collided with a bus, but at a lower speed. Also, a Tesla car ran into a truck in China in 2016. All these previous incidents with autonomous cars clearly demonstrate that they are not yet mature enough to be deployed on highways and all kinds of roads. No matter how many millions of miles driverless cars travel, a single incident significantly impacts the deployment and adaption of autonomous cars.

C. Social Challenges

The autonomous car technology brings significant benefits such as improved safety, traffic management, time management, ease of access and so on. Similar to other new innovations, the autonomous car is also susceptible to social risks and challenges [215], [216]. There are several risks involved with the proliferation of the autonomous car. For instance the adaptation of the autonomous car in our lives, errors that could lead to deadly accidents, and the humans' natural fear of change. Risk also has a social dimension for different groups of people. For example, the beneficiaries (vendors and service providers) of autonomous cars are not affected by the (possible) harm caused by the autonomous car whereas the consumers (who directly take risk) do not share to the same extent the benefits that the vendors do. In a nutshell, the social problems associated with autonomous cars is a dilemma because on one hand, as suggested by a recent survey [217], the consumers approve utilitarian moral decisions (the autonomous car should sacrifice the passengers for the greater good), but on the other hand, the same consumers would not prefer to ride in the same autonomous car. The study by Bonnefon *et al.* [217] concluded that a rational tradeoff is essential to choose the right kinds of algorithms among utilitarian and self-protective algorithms (in the case of moral decisions) for autonomous cars. The discussion on social challenges needs further research. However, in current discussions, we limit them to the most obvious social challenges (such as the behavior of people towards autonomous cars and the implications of autonomous cars on the society that include loss of jobs for drivers and loss of businesses) faced by autonomous cars. To this end, social challenges include dynamic human behavior, as well as ethical and moral challenges faced by the autonomous car.

1) Human Behavior: During the initial deployment stage, when both autonomous and non-(semi)-autonomous cars will occupy our roads, it will be important to understand human drivers' behaviors toward autonomous cars. Similarly, the driving pattern and behavior of autonomous cars will also influence their adoption. Thus, it is also important to know whether autonomous car users will be able to tune the autonomous car's behavior [218]. Another challenge concerns ethical issues. Humans possess the discretional power of judgment, whereas machines do not. The autonomous car technology is, in principle, developed for safety and comfort where the safety and security of its occupants must be the highest priority. This requirement leaves the automated car no room for mistakes or errors on the road. This requirement also means that the autonomous car by default will adapt to careful driving behavior. However, as we mentioned previously, human behavior is highly dynamic and therefore it will be quite challenging for autonomous cars to cope with diverse situations. Recently, an autonomous car experienced aggressive behavior from truck drivers [219] on the road and almost resulted in an accident. Coincidentally, the same vehicle experienced a fatal accident later [220]. Additionally, to mimic human behaviors, the autonomous car must be flexible in adapting to any unforeseen situation on the road. At the moment this feature, along with dynamic behavior, are not fully realized and more research is required in the fields of machine learning, artificial intelligence, and human psychiatry to empower autonomous cars to react safely without delay to unpredictable events on the road. It is also important to educate people about autonomous car technology, and in this context, service providers and auto makers should arrange trainings and/or tutorials for the public.

2) Ethical and Moral Consequences: "Right of way" rules are clearly well-defined universally and are applied in every country [218]. However, in some cases, these rules might be overturned by human empathy. Depending on the driving behavior, some drivers give way even though they have the right of way, and the opposite behavior also occurs. It will be very interesting to see what an autonomous car will do in such situations. To take this scenario to another level of complexity, let us consider an unforeseen emergency situation: suppose that a child chased a ball into the middle of the road in an urban locality. Will the autonomous car be able to swerve into either oncoming traffic but away from the pedestrian, threatening the lives of the autonomous car's occupants, or will it run over the child instead to make sure its occupants are safe? Will there be any way for the autonomous car to achieve the best outcome from the worst scenario? If so, will the autonomous car be able to decide on the best outcome? To make it worse, there is even a deeper moral dilemma faced by the autonomous car. Consider the mighty "trolley problem" [221], which exhibits a scenario where, "a conductor of a trolley has the choice of staying on the planned track and running over 5 people, or turn the trolley onto a track where it would only kill one person, assuming there is no traffic on it". In such a case, it is really important to know which moral basis the autonomous car will use to come to a decision. Furthermore, even if it is possible for the autonomous car to come to a timely decision, how does the underlying software get programmed to make such decisions? These are fundamental questions related to daily life that must be taken into consideration before the autonomous cars full deployment.

Nyholm and Smids [222] tried to separate the analogy of the trolley problem from the accident-algorithm of the autonomous car; however, the actual ethical problem still exists for the autonomous car. Thus, some of the situations are associated with ethical issues rather than technological ones. It is worth mentioning here that if an algorithm used by the autonomous car's software is fast and intelligent enough, then it mostly will decide in favor of applying the brakes instead of swerving into other traffic, vegetation, or pedestrians. Critics suggest that autonomous cars should adapt a combination of multiple ethical theories based on different parameters such as, but not limited to, maximizing utility, deontological ethics, morality, and so on to be able to make morally and ethically correct decisions while responding to an unforeseen but expected crash [223]. We also note that the driving behavior of some autonomous cars might also make its occupants uncomfortable or even offend the occupants in some cases such as, for instance, when aggressive users of autonomous cars feel bored with the polite or slow driving behavior of other autonomous cars and vice versa [218]. Therefore, accurately modeling the autonomous car's behavior dynamics is another challenge for the technology.

Despite the fact that the autonomous car will eliminate car crashes, improve economy, and provide consumers with various features and services [24], there are still social equity concerns and moral challenges that will somehow be at odds with the promise of autonomous car technology. We only focus on the economic issues here. The development of the autonomous car system will worry people in the driving profession because, for instance, taxi drivers might lose their jobs. According to a recent estimate, autonomous car technology, if successful, will cost roughly 5 million jobs in the U.S. alone [224], which comprises about 3% of the workforce. Furthermore, beyond drivers, a lot of other professions directly or indirectly related to automation will suffer. For instance, car washers, mechanics, auto engineers, and car dealers will all be impacted by the evolution of the autonomous car. Once autonomous cars pervade our roads, people might feel reluctant to own a car, because they will not need to perform typical tasks such as fueling, parking, maintenance, insurance, and so on when they can easily order a driverless car. Such a situation will clearly put pressure on governments and lawmakers to come up with acceptable alternatives and policies to the aforementioned problems.

Thus, with the proliferation of autonomous car technology, governments must offer alternatives to the people affected by this technology. These alternatives could include jobs, tax subsidies, and so on.

D. Policy Challenges and Recommendations

The proliferation of autonomous cars will provide a plethora of opportunities but, as we mentioned, it will also create new policy challenges for governments and lawmakers. The traditional mindset behind driving will change forever, because of the human exclusion from the equation. Policies and regulations currently in place when a human driver is present will need to be revised when a robot car drives itself [225], [226]. We need a clear, concise, win-win policy that not only has a positive economic impact, but also addresses consumers' concerns.

In November 2016, the U.S. DoT announced a federal policy on automated vehicles that covers different aspects of autonomous car development [227]. This policy announcement is considered a significant milestone in the development of autonomous cars. The policy describes details about all aspects of the autonomous car, including design, implementation, software, hardware, and security. Earlier in June 2016, the National Association of City Transportation Officials (NATCO), which represents more than 40 cities in the United States, also released a policy statement on automated vehicles (autonomous vehicles [228]). The focus of the NATCO policy statement was on the urban environment for automated vehicles and its after-effects. Furthermore, it also provided recommendations that will simplify the deployment process for autonomous car technology. NATCO provided the following key recommendations to federal regulators and state transportation departments:

1) plan for regularizing and deploying fully automated cars instead of connected vehicles;
2) plan road networks carefully, keeping in mind the proliferation of automated cars;
3) enforce security measures, including speed limits in urban environments to guarantee safety and security;
4) define clear and concise data-sharing requirements and regulations to ensure user privacy; and
5) design and build flexible traffic models to incorporate the change in paradigms and mindsets due to automated cars in mainstream traffic.

Another American non-profit policy think tank Research and Development (RAND) corporation also provided its insights into autonomous car technology and provided a comprehensive and detailed document [37] to assist autonomous car policymakers throughout the policymaking process. RAND recommended more funding for additional research on different functional and non-functional aspects of autonomous car technology. RAND also recommended subsidies and tax reforms to stabilize the fluctuation in costs of autonomous cars. The report further states that human lives should be the highest priority throughout the course of autonomous car development. Additionally, the judiciary system should also take into consideration the costs and other parameters related to both companies and autonomous car owners when ruling on cases related to incidents involving autonomous cars. Finally, the report from RAND also recommended that the policymaking process be less stringent, because the long-term effects of the policies on autonomous technology will decide its future.

Apart from governmental and other organizations' efforts to promote the next paradigm shift in transportation, individual efforts also have been made by the research community, resulting in some recommendations. For instance, Fagnant *et al.* [24] highlighted key aspects to standardization and regulation bodies for autonomous cars. Similar to the RAND report, [24] also highlighted the need for increased funding that will foster additional autonomous car research and streamline autonomous car technology with noteworthy results. Another important aspect is autonomous car certification. Although the U.S. DoT has been working on a joint policy that could be used for generic autonomous car systems [229], there are still several areas (such as testing and validation) that need guidelines and recommendations.

It is also worth noting that according to the U.S. NHTSA, state-level efforts have been made to legalize level 4 (fully autonomous cars with possible human intervention if needed) and level 5 (fully autonomous cars with no human intervention in any case) autonomous cars [230]. Policies and regulation impacting security, privacy, costs, services, and liability also should be given serious attention before deploying autonomous cars on a massive scale.

VII. Conclusion

Autonomous car is a rapidly evolving technology, and today many auto makers and other technical companies are experimenting with autonomous cars. An autonomous car's overall functional cycle falls into the following abstract categories: situational awareness, planning, control, and actuation. The major benefits of autonomous cars include, but not limited to, improving safety for both passengers and outsiders (pedestrians and other vehicles), new business opportunities, ease of use and convenience for people who cannot or do not want to drive, improved traffic conditions, and creating a consumer-centric experience. However, despite these benefits, there are still design and implementation issues that need to be addressed before commercial autonomous cars are fully deployed on the road. In this paper, we have conducted a detailed and comprehensive review of current state-of-the-art solutions in Section IV, design and implementation issues in Section V, and future challenges for the autonomous car technology in Section VI. We focused on research areas where the research results have been applied to the autonomous car domain so far. These areas include computer vision, learning, perception, planning, control, and decision-making. Furthermore, we also outlined some of the real-world tests conducted on autonomous cars.

We classified the design and implementation issues into the following categories, and we thoroughly investigated each one of them in detail: the autonomous car's cost, digital map construction, software complexity, testing, validation, and simulations. Besides these issues, other concerns remain and these include technical and non-technical challenges. As for the technical challenges, we discussed different standards (such as ISO26262) related to autonomous cars. We also reviewed aspects of safety and reliability, computational resources, accuracy of object detection, sensors management, decision-making, actuation, security, and privacy. Furthermore, we also discussed non-technical challenges such as diversity, consumer trust, the uncertain costs of autonomous vehicles, their operational robustness, complex liability paradox, and social challenges such as human behavior toward driving, plus ethical and moral consequences. Finally, we discussed policy challenges and offered recommendations to help designers and policymakers devise safe, reliable, and viable policies for autonomous cars' design, implementation, and deployment (which should also be acceptable to consumers). Despite the remarkable results achieved to date with autonomous car technology, it is still too early to speculate about the commercial phase of the autonomous car. Nevertheless, we believe that more research results will lead the autonomous car industry towards commercialization in the years to come. It is our hope that, moving forward, this paper provides some baseline for researchers who want to pursue research in the field of autonomous car technology.

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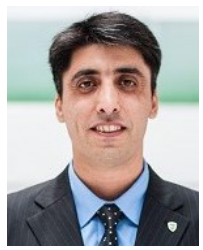

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