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Assessment of the state of the art in the performance and utilisation level of automated vehicles

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ABSTRACT

The progress of technology in our current world continues to advance each day, benefiting human beings in various ways. One significant development in recent time is the emergency of automated vehicles, which have the potential to revolutionise transportation. These vehicles utilise electric power, sensors, cameras and sound navigators to carry out their intended operations without causing environmental pollution. Currently, there are several autonomous companies, primarily located in California, cities like San Francisco (Cruise), Palo Alto (Tesla), Fremont (Pony.ai), Santa Monica (Motional), Mountain View (Waymo), and Foster city (Zoox). This paper aims to review the utilisation level and performance of autonomous vehicles, specially focusing on the goals set for 2023. By analysing various research studies and company profiles, this paper aims to provide insights into the current status of autonomous vehicles and their practical applications. It employs quantitative and statistical methods to extract valuable information from these studies. Also, this paper examines the state of the art in autonomous vehicles and the impact of gaps in machine learning algorithms, from perception to execution. The data used for this study are obtained from research reviews and updated profile of different companies. The assessment reveals a significant increase in research and development activities related to autonomous and automated vehicles across various disciplines since 2010. Specifically, the number of research studies on autonomous driving vehicles has increased from 302 to 2718, while studies on automated vehicles have increased from 1379 to 6085. In the Engineering discipline alone, there have been 601 studies on autonomous driving vehicles and 341 studies on automated vehicle-related research, which have increased to 2685 and 1865, respectively in the specified time.

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KEYWORDS
Automated vehicles; engineering discipline; environmental pollution; performance; utilization level

1. Introduction

The traditional transportation system is becoming increasing mixed-up and inefficient. According to the Vienna convention (UN 1968) many countries signed at a time ‘every moving vehicle or combination of vehicles shall have a driver’ and ‘every driver shall at all times be able to control his vehicle’. On 23 March 2016, a change to the Vienna Convention went into effect. As a result, ‘the driver, still in control of the vehicle, can be helped by a system under some conditions’ as long as the system can be overridden or shut off by the driver (Transport 2015). However, it has been stated that other changes must allow automated vehicles on roads in many countries. Mitchell (2015), proposes a ‘new deoxyribonucleic acid (DNA)’ for automobile in their book ‘Reinventing the Automobile’, envisioning vehicle that are electrically driven, powered by electric motors, energised by electricity and hydrogen, electronically controlled, and intelligently interconnected with the goals of a sustainable future with zero emissions, renewable energy, crash avoidance, safe social networking while driving, autonomous driving (as an option), varied designs, and shrouded in mystery. Early forms of automation include electronic stability control (Af Wåhlberg and Dorn 2023), lane departure warning (Navarro et al. 2024), adaptive cruise control (Hidayatullah and Juang 2021), lane keeping and centring (Elzen 2015), pedestrian detection (day/night), self-parking (Thunyapoo and Ratchadakorntham 2020, traffic sign and signal detection (Bai et al. 2023; Qiao 2023), and vehicle-to-vehicle communication (Dhurve and Soman 2021; Muslam 2024).

According to the Society of Automotive Engineering (Williams 2021), vehicle automation has been adopted globally. It was updated level by level, step by step, for more improvements. Implies six levels of automation (from 0 to 5) are differentiated based on the onboard driver assistance systems, i.e. the distribution of driving task between the vehicle and the driver. On Table 1, some explanations are provided to offer an overview of self-driving vehicles. On level 0, there is no automation, however, on level 1, some automation is possible, with the car controlling either steering or acceleration/braking. A combination of autonomous functions on level 2 enables the automobile to take over steering and acceleration/braking tasks at the same time. On levels 3 and 4, the automobile generally accomplishes everything that the driver

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Table 1. Impacts of AV on cities transportation/pros(right) and cons(left) (Maheshwari 2018).

• For pedestrians, • For cyclists.	Less Mobility	How will AVs impact cities?	More mobility	• For people with disabilities. • For the ageing population. • For children.
• Slower due to over cautious driving behaviour. • Longer travel distance due to sprawling or remote.	Increased travel time		Time efficient	• No more parking hassle. • Door-to-door connectivity. • Productive use of in-vehicle time.
• Car-dominated streets. • Increased sprawling.	Efficient use of space		Space efficiency	• Narrow lane width. • Fewer street signs. • More capacity due to smaller headway. • New urban infill potential (parking garages, streets)
• Security issues due to hacking attacks. • Loss of privacy.	New safety concerns		More safety	• Fewer road accidents.
• Increased VMT and congestion due to induced demand. • Public transportation walking and cycling may become less frequent.	Environmental Concerns		Environment friendly	• Fuel saving due to efficient driving. • Better congestion management. • Electric mobility.

would have to do otherwise, with the exception that on level 3, the automobile is unable to do everything in order to notify the driver when he or she must regain control. In contrast, no control may be reclaimed by the driver at level 4. The third and fourth levels of automation are meant when talking about self-driving or autonomous cars in this study because both include cars that are generally capable of doing all driving tasks on their own and in level 3 only in some unknown situations the driver has to do the driving again. This paper contributes a comprehensive assessment on autonomous vehicles state of the arts based on different disciplines discussed in Section II. Picking five different research mortar apparatuses with different research disciplines complete this study paper.

It covers the sustainable systems of the world, which encompasses a discussion that covers status of zero tailpipe emission vehicles. The first Figure 1 below shows more clarification symbolically on the levels of AV.

The automotive industry and media have muddled the language used to discuss automated driverless systems. Redundantly, the terms autonomous, driverless, and self-driving conceal more than they reveal. To clarify, SAE International created definitions for various levels of automation, which were elaborated on, and put them on a scale of decreasing reliance on the driver. The hierarchy offers some unexpected results. Level four automations, for example, may be more tractable than the preceding level, which is level three. The same is true for the next, i.e. level five automated systems-electronic chauffeurs capable of handling every driving situation without human intervention, which are decades away.

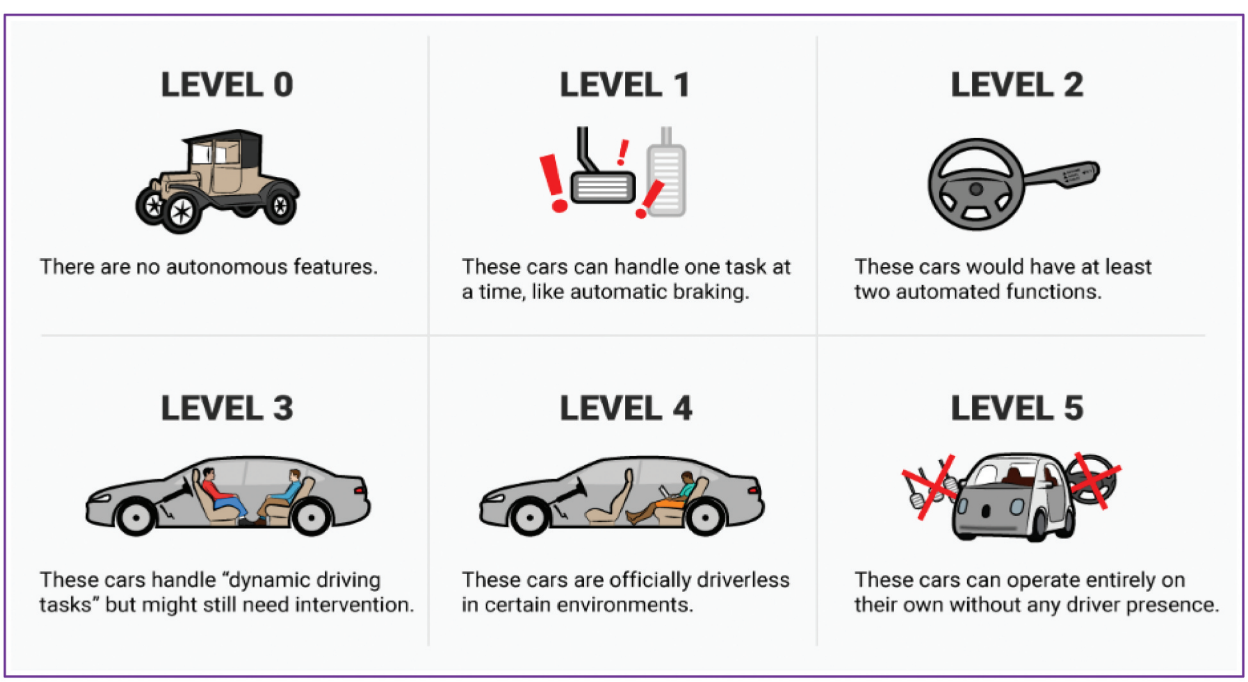

Figure 1. Comparison of vehicle operating models of automated driving levels (Williams 2021).

2. Contributions

This study attempts to provide a comprehensive and organised ways of the state of the arts to automated vehicles. It focuses on automated and/or autonomous vehicles research related status with different disciplines by selecting five goals, i.e. book chapters, conference abstracts, encyclopaedias, research papers and reviews. This study aims to fill the gap by providing a comprehensive overview of the existing literatures and publications on sustainable engineering. In addition, we discuss the existing conditions from both societal and industrial perspective. This paper covers companies, the state of arts in their present condition, gaps and challenges related to machine learning algorithms of automated vehicles plus their vulnerability, and their implementations. Finally, we outline future research directions as per our findings.

3. Methods

In this review work, the literature coverage is considered in comparison of open scientific sources published recently, which is not greater than 5 years except some conventions and mandatory reference books. To obtain sufficient coverage of the works related with AV, we used the following scientific databases to search through the literature: Scopus, Elsevier, Google scholar, Hindawi, Springer, MPDI, Research gate, SAGE, BASE, SCISPACE, semantic scholar, and others. To fit the objectives as uttered on the titles, we used different English language keywords such as autonomous vehicle, automated system, AV companies, controllers, AV environmental perception, impacts of AV, AV machine learning algorithms etc. Analytical systems for scrutiny were part of it, and current statistical data were used to assess the status of AV plus plots in graphical style on an Excel sheet.

4. Theories on positive and negative aspects of transportation automation

As per scholars for the past 20 years, there has been an enormous advancement in the field of automated driving technologies.

Frankly speaking, it significantly increases the vehicles' active safety and efficiency from an energy saving point of view. Thus, now a day its frontier in automotive engineering research, a new path of the automobile industry and beside this one it's a new source of financial growth for stakeholders (Teixeira, d'Orey, and Kokkinogenis 2020). At present, the benefits or hazards of AVs are just hypothetical. For AV transitions to have a substantial impact, nearly full market penetration of automated vehicles is required, and predictions for such a lengthy time horizon are necessarily uncertain (Maheshwari 2018). Different challenges such as traffic conditions (Funke et al. 2016; Zhang, Zhao, and Jiao 2023) in which they are expected to drive with other autonomous vehicles on the same road while also monitoring pedestrian movements, road conditions (Park, Lee, and Han 2015), while it operates on automated vehicle roads it should be recommended to follow the predefined ways; Accident liability (Uzair 2021), implies when they react to situations when their attention is desired, it may be too late to prevent the conditions. Lidar and Radar effect (Bilik et al. 2019; Hassan 2022) can be shown as, Radar cannot pass through walls with high accuracy because the beams scatter as they reach the wall, resulting in a false positive which means information is incorrect and other artificial and emotional intelligence is affected. Table 1 shows the compiled pros and cons of automated vehicles as follows.

At the moment, the pros or cons of AVs are just hypothetical. For the AV revolution's effects to be seen, almost full market penetration of fully autonomous cars is required, and predictions for such a lengthy time horizon are necessarily uncertain. Each mobility, time, space, safety, and environmental concerns have own impact whether positive or negative. As is obvious, the benefits of automation might just as readily translate to threats, depending on the underlying assumptions. Planning and decisions might improve one region while jeopardising another. Many concepts of urban design have been proposed that address both sides of the spectrum. Concepts on Table 1 described as follow.

4.1. Mobility

It concerns allowing some people to move while confining others (Millard-Ball 2018). Unfortunately, AVs provide previously unserved populations with unfamiliar mobility alternatives, such as those with impairments, elders, and children. However, in order to maximise the effectiveness of AVs, even more limitations on walkers and bicycles, such as grade separated sidewalks or barriers, may be imposed, effectively limiting their movement.

4.2. Time

Effective use of time or travel time which is very mandatory point. Travellers may save time by using a better-managed and integrated transportation systems, parking, and more productive in vehicle time (Litman 2023; Lutin 2015). On the other hand, increased demand from better managed traffic may, ironically, contribute to congestion. New demand from individuals who were previously unable to drive, as well as excursions away from healthy modes like walking and cycling, might all contribute to congestion.

4.3. Space

It determines either better expansion or better spatial efficiency. In perspective, AVs condition will be predicted as it occupies less space and can drive with higher precision, hence current street design regulations should be altered. For example, changing four lane roadways to five lane highway with the help of minimum cost of investment (Hayeri 2015). However, the research of (Litman 2018) indicate that as AVs become available, the attraction of suburban residential districts that are greener or cheaper would grow.

4.4. Safety

Because the majority of road accidents are caused by driver error, AVs are assumed to have the potential to drastically reduce accidents (Fagnant and Kockelman 2015; Litman 2020). However, there may still unanswered problems regarding culpability in the event of an accident, its vulnerability to cyber-attacks, and loss of privacy owing to continuous location tracking.

4.5. Emissions

Shorter headways, coordinated platoons, and more effective route choices are predicted to allow AVs to use existing roads and junctions more efficiently, resulting in fuel savings (Fagnant and Kockelman 2015; Hayeri 2015). On the other hand, we can predict increasing overall travel distance owing to expansion, additional non driver travel demand, and stimulated demand due to travel time reductions, decreased congestion, and, paradoxically, fuel savings.

On the other hand, the sustainability of the system influences the benefits of AVs through emissions, accidents, traffic congestion, and legislation. First, emissions cause environmental hazards to living things. When compared to a human-driven vehicle, autonomous vehicles utilise less gasoline and energy. The majority of gas is consumed when travelling at high speeds, stopping, and often re-accelerating. Self-driving vehicles eliminate these elements from their driving style, resulting in less gasoline used or battery power utilised, and hence less air pollution. Driverless cars also imply fewer automobiles per family. One autonomous car can literally take you to all of your places, so families may avoid having two or three automobiles to accommodate the demands of each individual. It is also projected that as driverless car technology advances, the weight of automobiles will decrease because of lower batteries, modifications to the engine, and a reduced need for hefty safety features. Second, safety is most important for human survival. For sure, crashing is caused by humans, not cars. Human drivers are the most dangerous component of the driving experience, whether due to reckless driving, human mistakes, texting, driving, or simply being preoccupied behind the wheel. The third is traffic congestion, which is another title. In addition to pollutants and city haze, most city inhabitants find traffic congestion inconvenient. Highways and thoroughfares take up valuable urban real estate, leaving little to no space for pedestrians, bicycles, or parks. When all vehicles on the road are autonomous, congested city streets and highways will become a distant memory. Lastly, while the technology appears to be too attractive in terms of possible advantages and enhanced safety, the government remains concerned about autonomous vehicles. Driverless automobiles are now permitted in some developed countries, such as California, Michigan, and Florida, other states by considering legislation. Therefore, introducing autonomous vehicles is part of sustainable engineering for environmental conservation.

Even though the system will be designed to extend human life by reducing risks through crashes that are hunting human beings in millions. Colleagues (Sharath and Mehran 2021) from Canada state two basic plausible cases resulting in a crash: environmental perception and motion planning. If a crash has occurred, the mean is summarised by three points. First, both are imperfect. Second, it could be solely attributed to erroneous environmental perception and lastly, sole imperfections of motion planning, while the other is reversed. They are considered non-sociable because they cannot interact with other drivers by definition. This results as they fail to consider other vehicles, for example, during mergers. On the other hand (Jiang, Xie, and Evans 2023), the systems of automated vehicles, even though they depend on AI, it is difficult to implement courtesy in the algorithms. Based on the research analysis done on traffic accidents from 2015 to 2017 (Petrović, Mijailović, and Pešić 2020), inspects the severity of rear end collisions on automated vehicles is greater than that on conventional vehicles based on the assessment and results, the collision of automated vehicle is 35.9% greater than the crash with conventional vehicles. This simply implies that rear end collision of an AV is higher comparatively based on the US state of California DMV reports. Figure 2 shows figurative statistics of the accident level comparison.

In Figure 2, on the other hand, the data from the same source from 2015 to 2019 shown on (Song, Chitturi, and Noyce 2021) explains that the most common types of AV collisions were rear-ended (62%) and sideswipe (21%). Injuries were reported in 12% of the collisions, with no distinction between light and major.

4.6. Automated vehicle implementation predictions

As seen via the lens of AV technology, most of our auto makers are working on SAE-3rd and SAE-4th level vehicle (SAE 2023). It has been said, might be available on the road in short terms. However, in spite of the optimistic announcements made by some companies, most forecasts agree as shown below in Tables 2 and 3. It might take a long time to make SAE level 5, which means fully automated vehicles, and much more to achieve a significant implementation rate with the whole vehicle fleet (Martínez-Díaz and Soriguera 2018).

Victoria Transport Policy Institute forecasts the development and implementation of autonomous vehicles from various perspectives, as shown in Table 2. The assumptions include the availability of level 5 autonomous vehicles, which is discussed in Section IV, in the late 2020s. However, it should be noted that these vehicles are initially expensive and have limited performance. Additionally, without regulations in place, it may take several decades for the market to become saturated with autonomous vehicles, as some drivers may still prefer human-operated vehicles due to cost and personal preference. These estimations are a compilation of (Grush and Niles 2016; Lavasani, Jin, and Du 2016; Simonite 2016).

Different research reviews state, a sort of factors that influence the deployment of self-driving vehicles. Litman (2023) introduces those factors like the rate of technological advancement or the speed of technological developments is somehow long i.e. before automobiles may run independently under all usual settings, significant technological advancements are required (level-4). According to the present conditions, the most outstanding level, which is last in our review, will be available in 5 to 25 years. Second, their testing and regulatory approvals are mandatory in autonomous vehicles. Although it is currently under development, it may take many years for these standards to be implemented in most jurisdictions, and more time will be needed for large-scale testing. The others include Incremental costs,

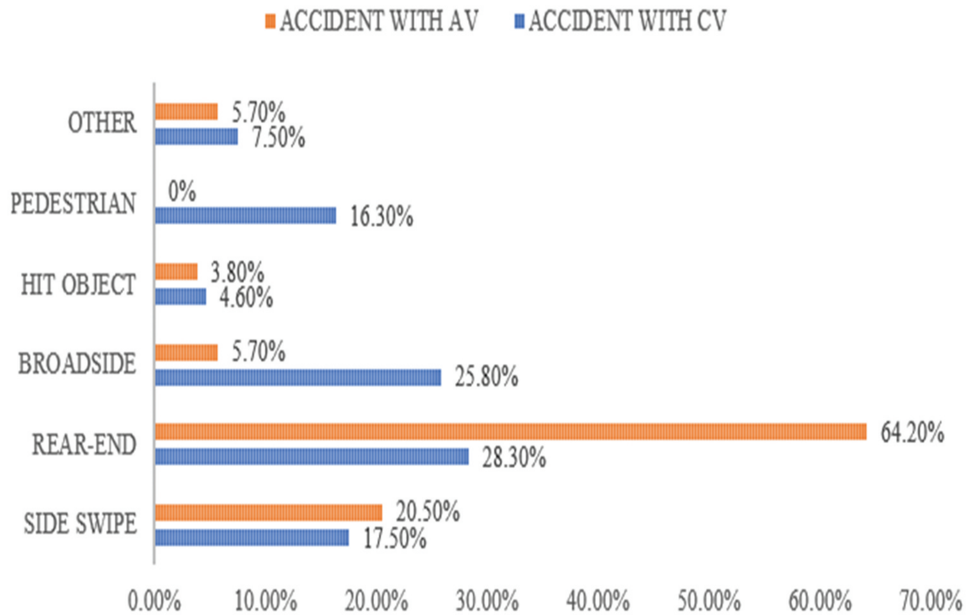

Figure 2. Performance of the automated vehicle from the conventional vehicle perspective in rear-end collisions.

Table 2. AV implementation stage and its impacts (Litman 2023).

Stage	Decade	New Sales	Fleet	Travel
Development and testing	2020s	0%	0%	0%
Available with large price premium	2030s	2–5%	1–2%	1–4%
Available with moderate price premium	2040s	20–40%	10–20%	10–30%
Available with minimal price premium	2050s	40–60%	20–40%	30–50%
Standard features included in most new vehicles	2060s	80–100%	40–60%	50–80%
Saturation (everybody who wants it has it)	2070s	–	–	–
Required for all new and operating vehicles	–	100%	100%	100%

Table 3. AV implementation predictions set its levels per year.

Source	SAE-L4	SAE-L5	CAV Environment
Underwood (2014)	2019 – 2024	2025 – 2035	240–2060
Godsmark and Kirk (2015)	2020	2020 –2025	2020 – 2030
Shladover (2016)	2020 –2030	2075	–
Zmud and Goodin (2017); Zmud and Sener (2017)	2021	2025 –2030	–
Bloomberg (2017)	2018–2020	2028–2030	2040–2060
Litman (2018)	2020 – 2030	2020–2040	2060–2080
Kuhnert and Stürmer (2018)	2020–2030	2025–2030	–
Gehrke, Felix, and Reardon (2019); Steven (2018)	2018–2021	2018–2021	2040–2050
Ssctcc (2018)	2018 – 2020	2040–2050	2040–2060
Shaheen and Totte (2018)	2018–2021	2023–2040	2045–2070

service quality and affordability, consumer travel and housing preferences and development practices. The other very crucial point is public policies, which are another backbone for the implementation of autonomous vehicles. Chen et al. (2022) target to synthesise on the past research regarding public acceptance attitude towards AVs and elaborate significant issues such as the uncertainty of AV adoption experiments, policy implement and action plans, AV related infrastructure uncertainties and demand models as future approaches for analysing AV consequences.

On the other hand, when it is seen from an AV technological perspective, most of our auto makers are working on SAE-3rd and SAE-4th level vehicles. As it has been said, might be available on the road in short terms. However, in spite of the optimistic announcements made by some companies, most forecasts agree as shown in the below tables. It might take a long time to make SAE level 5, which means fully automated vehicles, and much more to achieve a significant implementation rate with the whole vehicle fleet.

Table 3 shows different data sources with different points of view on their implementations depending on their own reasons for SAE-L4, SAE-L5 and CAV environmental setups for applications. On the other hand (Zhao et al. 2021), highlights and emphasises potential improvements to the high-level driving strategy design by classifying existing autonomous vehicle driving to defensive driving strategies, competitive driving strategies, negotiated driving strategies, and cooperative driving strategies.

5. Results

Before explaining the statistical conditions, most researchers are upgrade the system operations by compiling those mandatory components. Perception of execution steps may pass through different struggling and hardy ways even though the operation could be completed in a second. Making decisions is one of the most difficult tasks that automated vehicles perform, especially in awkward situations. It may include prediction, path planning, and obstacle avoidance. All of which are based on previous perceptions done (Martínez-Díaz and Soriguera 2018).

Figure 3 above under this section (V), explains the processes that take place in automated vehicles input to output, following steps sequentially form sensors, perception, planning and decision, motion and vehicle control, and the actuators that take place for operations cooperatively one to the others.

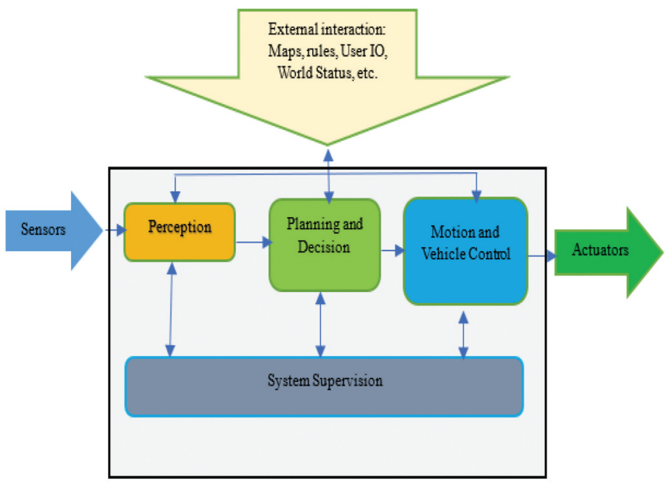

Figure 3. Input to output process of the AV.

Since 2010, there has been an increase in the involvement of different disciplines in autonomous and automated vehicle areas. Our focus is on 2010 and beyond, targeting to provide the latest information regarding these vehicles. Figures 4–7 below show research on autonomous and automated vehicles in all disciplines and engineering disciplines until the end of 2022. Autonomous vehicles, which are self-driving and can have self-decision capacity, are researched in different disciplines as follows: All disciplines i.e. Engineering, Computer Science, Social Sciences, Environmental Sciences, Energy, Decision Sciences, Medicine and Dentistry, Biochemistry, Genetics and Molecular Biology, Business, Management and Accounting, Agricultural and Biological Sciences are included in the research areas. Engineering is one of the target disciplines for our study. By defining their areas of application and similarity, the research is conducted by synonyms for different reasons. The basic reason this can be done in this area is to get acceptance from different h-index publishers around the world. Therefore, autonomous driving vehicles Figure 4 and automated vehicles Figure 5 in this discipline's research are also increasing. Let's see the automated vehicle research done from 2010 on, like the figures shown below with all disciplines.

Figure 4, depicts a decrease in the number of research articles published on autonomous driving vehicles across all disciplines from 2010 t0 2011, followed by a slight increase from 2011 to 2018. From 2018 to 2022, the variation is doubled (1164 to 2718), while conference papers are almost the same. In Figure 5 below, the same variables were used for testimony, but the subject was automated vehicles.

Autonomous driving vehicle Figure 6 and Automated vehicles Figure 7 with engineering discipline may include almost all of them, such as Mechanical, Environmental, Computer, System, Electrical, Industrial, Electronic, computer science and Engineering, Civil, Aerospace, Nuclear, Safety and other disciplines included in these scenarios shown on Figures 6 and 7.

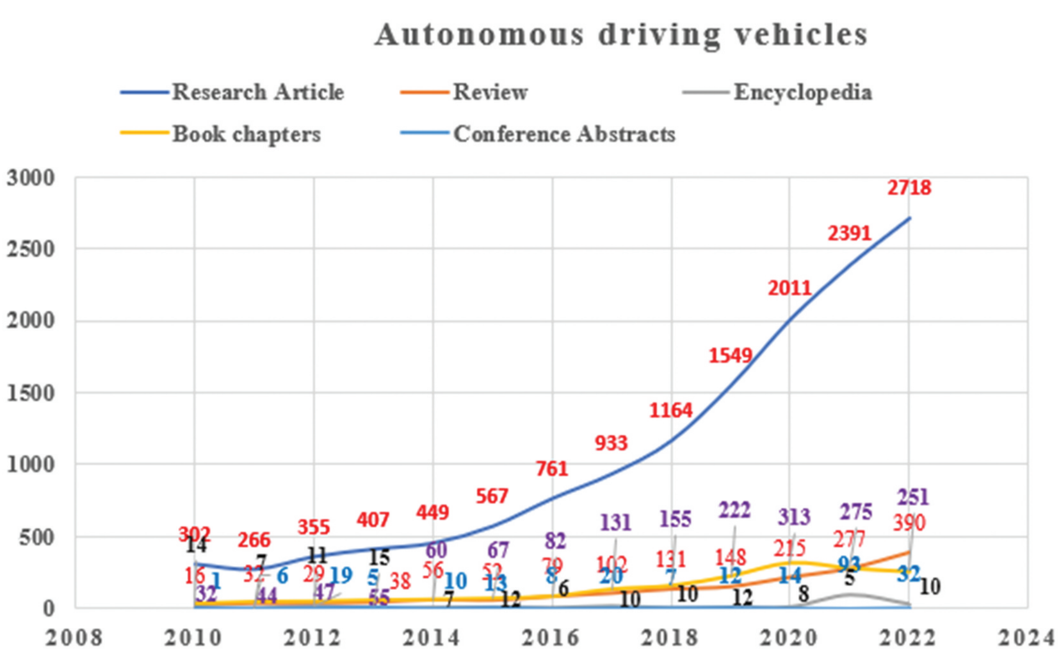

Figure 4. Autonomous vehicle driving all disciplinary research status.

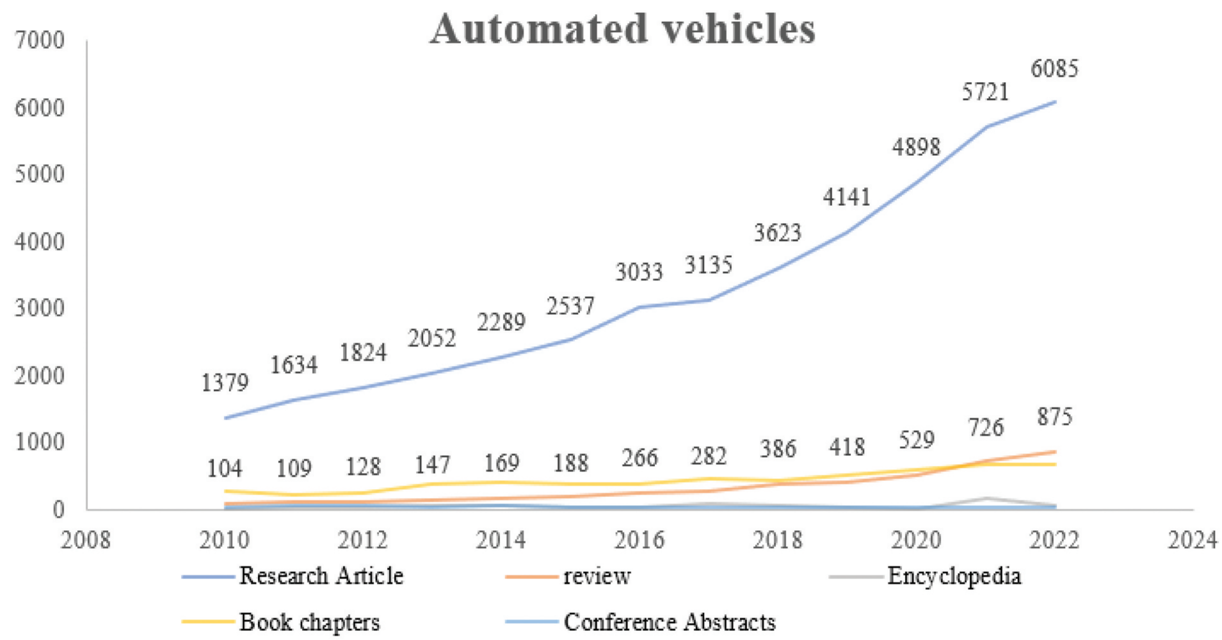

Figure 5. Automated vehicle for all disciplinary research status.

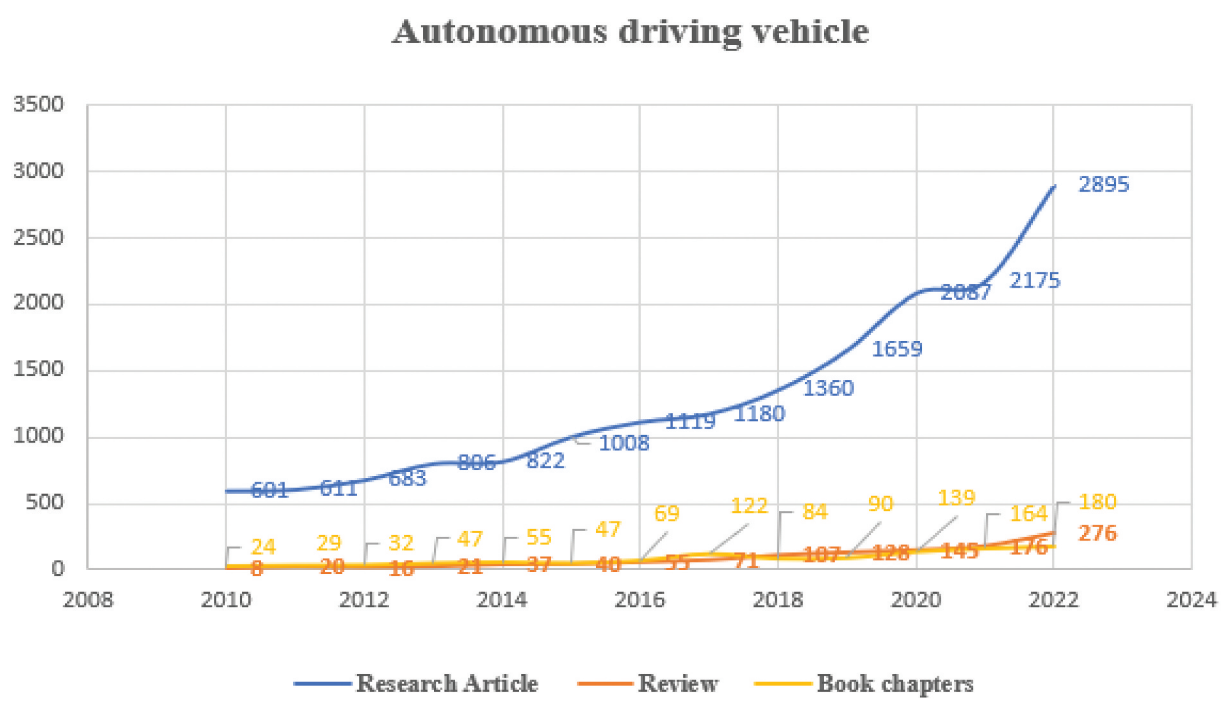

Figure 6. Autonomous vehicle driving engineering (only) discipline research status.

These have been collected by survey done with the biggest data holding institution with immense guarantees called backbone for researchers worldwide, which is Science direct.

5.1. Current companies in autonomous vehicle research and utilization level

There are more than 55 companies of AV for both software and hardware installation, however there are no commercially viable autonomous vehicles that go beyond 2nd and 3rd automation. It worth nothing that new companies are challenging conventional manufacturers, while some are already on the market, such as Tesla and others, are testing and adjusting different setups for the future. Test driving, on the other hand, is already common. In late 2009, Nevada granted Google permission to test autonomous vehicles. In Europe, countries such as Germany, the Netherlands, and the UK allow AV testing. On the other hand, a number of federal states in the US have approved or amended rules to enable autonomous test driving under specific situations. It is unforgettable that in 2018, Singapore completed a test of self-driving taxis. Japan intends to use driverless taxis on

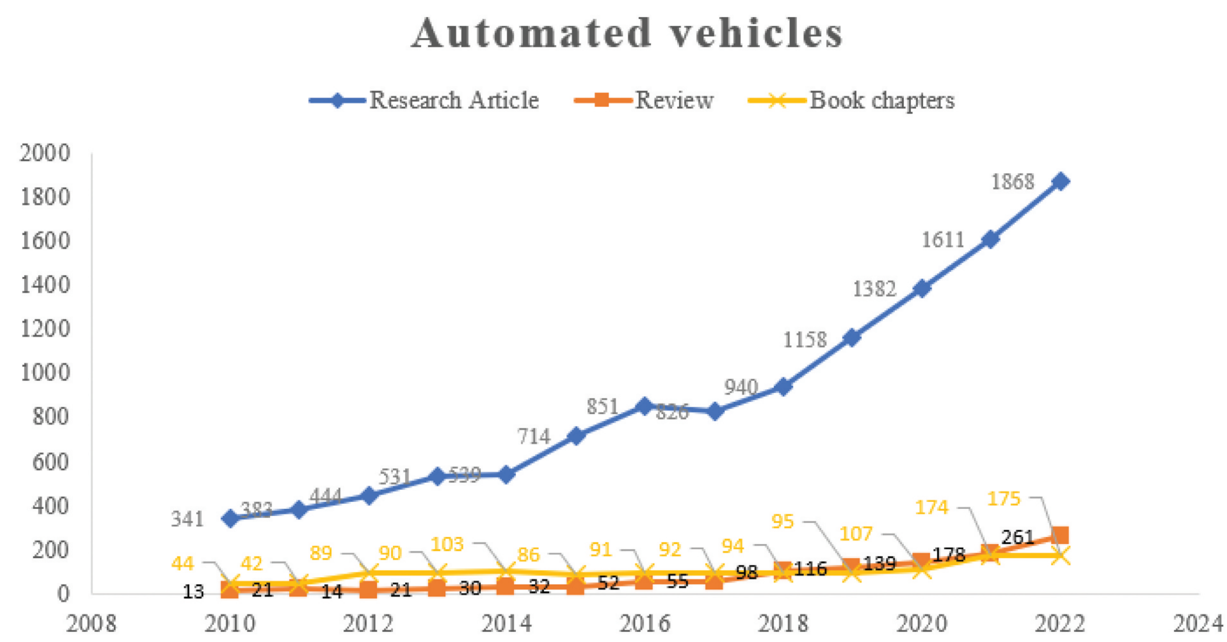

Figure 7. Automated vehicle engineering discipline (only) research status.

a significant scale during the 2020 Tokyo Olympics. Furthermore, autonomous buses are used in a various location, mainly in controlled environments. There are about 55 companies with autonomous vehicle research status in our current world. Most of them are working on software for AI, while others are on the technical side. A summary of their research status is shown in Table 4.

5.2. Gaps and challenges in machine learning algorithms for AV driving applications

Algorithms for AVs are inputs because they operate without human intercession. Lack of these properly set algorithms makes the system faulty in some actions. This deficiency includes; techniques and sensors used in AV, uninclusiveness of different country scenarios, and problems with some system components such as varying climatic conditions, especially in the case of navigation systems. Radar interference, climatic, traffic, and street conditions are the front facing challenges in navigation systems (Prasath 2020). Beyond those, security risks of adversarial attacks, which are not considered primarily a safety, rather a security limitations and procedural safeguards for machine learning safety, which focus on diminishing the misuse of system due to lack of instructions and unawareness (Carlini 2017; Mohseni 2019). Obviously stated, machine learning is a subtype of artificial intelligence that enables users to equip their systems to operate in the grey region of fuzzy logic, which perhaps looks like human intelligence. This problem with machine learning algorithms may affects the entire operating system. The reason behind this is that all localisation, tracking, and detection are performed by first contact with the objects, which is called perception. All other followers are enhanced either positive or negative ways. This implies that all identification, decision, control, and executions are succeeding. Thus, still today, there is lack of very successful and matching algorithms that are 100% proper for completely remove errors and made transportation more comforted in current genuine world. But hope for future transportation systems, it will happen.

5.3. Gaps and challenges with machine learning methods include the following

5.3.1. Data quality and quantity

A large amount of high-quality data is required to train effectively. These data can be difficult and expensive to collect, especially for rare or unexpected events (Hussain and Zeadally 2018).

5.3.2. Bias

Machine learning algorithms can learn biases from the data on which they are trained. This can lead to autonomous vehicles making discriminatory or unsafe decisions (Danks 2017).

5.3.3. Explain ability

It can be difficult to explain why machine learning makes a particular decision. This can make it difficult to identify and fix errors in the algorithm (Kolekar et al. 2022).

5.3.4. Robustness

Machine learning algorithms can be vulnerable to adversarial attacks, where carefully crafted inputs are designed to fool the algorithm (Fényes et al. 2021; Phan 2023).

5.3.5. Cybersecurity

AVs are vulnerable to cyberattacks, which could cause them to malfunction or even be hacked (Aurangzeb 2023; Giannaros et al. 2023; Sadaf et al. 2023). It is important to develop robust cybersecurity measures to protect AVs from these threats. Ghosh et al. (2023) provides

Table 4. Summary of automated vehicle companies and their background.

Companies name and year of founding	Country	Current status and level of autonomy
1. ABB (1988)	Netherland (Zurich)	Manufactures technologies for self-driving cars, industrial automation, robotics, and electrification.
2. AIMOTIVE INC (2017)	California (Mountain view)	This company is an AI software developer for autonomous vehicles. The company's software is designed to enable self-driving cars to perceive their surroundings, make decisions, and plan their routes. Audi, Hyundai, and Mercedes-Benz use Aimotive's software.
3. APEX.AI (2015)	California (Mountain view)	Developer of open-source software for autonomous vehicles. The company's software is designed to provide a common platform for developing and deploying autonomous driving applications. Bosch, Continental, and Toyota use their software.
4. APOLLO AUTONOMOUS DRIVING USA LLC (2017)	California (Sunnyvale)	Subsidiary of Baidu, a Chinese technology company. Develops autonomous driving technology for use in passenger cars, trucks, and busses. Testing its technology in the United States, including Phoenix, Arizona, Pittsburgh and Pennsylvania.
5. APPLE INC (1976)	California (Cupertino)	It is American technology. It is developing autonomous driving technology for its own cars. Not announced any plans to release, but the company is believed to be making significant progress.
6. ARITY (2016)	US (Chicago)	Originated in insurance and, is ideally positioned to foresee and manage risk through data and behavioural insights.
7. AURORA (2017)	California (Mountain view)	Aurora intends to introduce Horizon, the first autonomous service powered by the Aurora Driver, in 2024, with the goal of bringing safety, value, and efficiency to carriers and fleet owners. Uses multimodal fusion algorithms (CNNs, RNNs, RL).
8. AUTOX (2016)	California (San Jose)	AutoX provides software solutions for self-driving cars. The company offers a camera-first self-driving solution and self-driving vehicles based on autonomous driving technology. AutoX was the first firm in Shenzhen and Shanghai to offer a fully driverless robo-taxi service on public highways, covering the world's largest driverless territory.
9. BEEP (2022)	California (Mountain view)	It is developer of self-driving shuttles for use in low-speed environments such as college campuses, airports, and retirement communities. Shuttles are currently used in several locations across the US.
10. BLACK SESAME TECHNOLOGIES (2018)	California (Santa Clara)	Develop AI chips for autonomous vehicles. Designed to provide the high-performance computing power required to run complex autonomous driving algorithms. It is partner with SAIC Motor and Dongfeng Motor.
11. BLUESPACE.AI, INC (2020)	California (Mountain View)	Developer of LiDAR sensors for AVs that helps to create a 3D map of the surrounding environment. Partnered with Ford and Hyundai.
12. BOSCH (1886)	California (Sunnyvale)	A German company, is developing autonomous driving technology for use in various vehicles, including passenger cars, trucks, and busses. Partnered with Daimler, Volkswagen, and Volvo.
13. CLOUDMADE (2007)	UK (London)	Develop, deploy, and integrate smart solutions for the automotive industry and deliver smart real-time suggestions to a desirable prototype, to increase the adoption of ACC features among the drivers.
14. CRUISE (2013)	California (San Francisco)	The corporation operates 100 robotaxis in the city as of September 2022 and plan to expand its fleet to 5K however, it has generated criticism. Uses the ensemble learning algorithm.
15. DiDi RESEARCH AMERICA. LLC (2018)	California (Sunnyvale)	A Chinese ride hailing company. Developing autonomous driving technology for use in own ride-hailing services. Partnered with Toyota and Honda.
16. EMBARK TRUCKS (2016)	California (San Francisco)	It develops self-driving software for the automobile industry that can transform any fleet into an autonomous one. We are collaborating with the trucking industry to integrate self-driving technology into their operations as seamlessly as possible.
17. GATIK AI INC (2021)	California (Mountain view)	Developer of autonomous driving technology for use in trucks. It is designed to enable trucks to make short-haul deliveries between warehouses and distribution centres. Operating in some locations.
18. GHOST AUTONOMY (2019)	California (Mountain view)	It is an American autonomous driving company. It is based on a novel approach to AI that it claims is more efficient and scalable than traditional approaches.
19. HAAS ALERT (2015)	Illinois (Chicago)	The safety Cloud integrates first responders, towing and recovery services, and road workers with vehicles and motorists to provide real-time digital notifications that avert collisions and improve overall road safety.
20. HELM.AI INC (2021)	California (Mountain view)	It develops unsupervised learning technology for AI and autonomous vehicles. It is designed to allow AI systems to learn from data without the need for human annotation or simulation.
21. IMAGRY INC (2016)	California (Mountain view)	The company develops computer vision software for autonomous vehicles. The software is designed to understand AV surroundings and make safe decisions.
22. LUMOTIVE(2017)	Washington (Redmond)	Lidar 2.0 production for consumer, mobility, and industrial markets.
23. MAGNA INTERNATIONAL (1957)	Michigan (Troy)	Actively upgrading and working to be first (Magna 2023)
24. MAY MOBILITY (2017)	Michigan (Ann Arbor) —	On April 2023, the first inauguration of Arizona's, on the demand of public transit service using AVs in the retirement town of Sun city, was announced. The power will be transit tech. (via the global leader).
25. MERC BENZ (1886)	California (Sunnyvale)	It is a German automaker that is developing autonomous driving technology. The company's technology is currently in the testing phase, and, it is expected to be available in production vehicles in the next few years.
26. MOBILEYE (1999)	California (Sunnyvale)	An Israeli company. Develops computer vision and machine learning technology for AVs. Mobileye's technology is used in autonomous vehicles from a various automaker.
27. MOTIONAL (2020)	California(Santa Monica)	Developing self-driving vehicles with lidar and more than 30 camera and radar sensors to ensure 360° sight and object identification.
28. NAUTO (2015)	California (Palo Alto)	Nauto is the only real-time, AI-enabled driver and fleet safety technology in the mobility ecosystem that can predict, avoid, and reduce high-risk occurrences. Nauto's machine learning algorithms continually improve and influence driver behaviour before events occur by analysing billions of data points from over 1 billion AI-analysed video miles.
29. NIO USA INC (2017)	California (San Jose)	A Chinese automaker that develops electric vehicles. It also develops autonomous driving technology. It will be in production in a few years.

(*Continued*)

Table 4. (Continued).

Companies name and year of founding	Country	Current status and level of autonomy
30. NISSAN (1933)	California (Sunnyvale)	Japanese automaker. The company's technology is currently in the testing phase and, it is expected to be available in production vehicles in the next few years.
31. NODAR (2008)	Massachusetts (Boston)	NODAR uses triangulation and widely spaced cameras to calculate depth at a great distance with high precision. It introduces low-cost, high-performance, long-range 3D sensing to the ADAS and AV businesses, as well as other verticals where performance vs. price must be extremely high.
32. NURO, INC (2016)	California (Mountain view)	Develops autonomous delivery vehicles. Their vehicles are designed to deliver goods to customers without the need for a human driver. Partnered with retail and food delivery industries.
33. NVIDIA CORPORATION (1993)	California (Santa Clara)	American multinational company. The company is developing AI and autonomous driving technology next to GPUs for gaming and professional markets.
34. OUSTER (2015)	California (San Francisco)	Ouster is a global leader in high-resolution scanning and solid-state digital lidar sensors, as well as Velodyne Lidar sensors and software solutions for the automotive, industrial, robotics, and smart infrastructure industries.
35. PEGASUS TECHNOLOGY HOLDINGS (2021)	California (Mountain view)	An American technology company is developing a lidar-based system that it claims is more accurate and reliable than traditional camera-based systems.
36. PLUSAI, INC (2017)	California (Sunnyvale)	A Chinese company that develops autonomous driving technology for trucks. It is currently in the testing phase.
37. PONY.AI (2016)	California (Fremont)	The first AV driving company to obtain a taxi licence in China. It is third behind Waymo and Cruise in the number of miles driven by 2021. Uses multitask learning type algorithms. L4-autonomy.
38. QUALCOMM TECHNOLOGIES, INC (1985)	California (San Diego)	It designs and manufactures semiconductors and software for the automotive industry, as well as developing AI and autonomous driving technology.
39. RIDECELL INC. (2015)	California (San Francisco)	The company develops software for ride-hailing and car-sharing services. The company's software is used by a various company, including Car2Go, Via, and Lyft.
40. RIVIAN (2009)	California (Irvine)	Working on autonomous vehicle technology called "Driver +".
41. SEEVA TECHNOLOGIES (2017)	Washington (Seattle)	SEEVA Technologies develops vehicle visibility systems. SEEVA's technologies improve the most cutting-edge automobile experiences, including applications in driverless cars and advanced driver support systems for passenger and commercial vehicle lineups.
42. SWIFT NAVIGATION (2012)	California (San Francisco)	Swift Navigation's lane-level positioning manufacturing solution was built to scale for automobiles and was geared for autonomous driving.
43. TELENAV, INC. (1988)	California (San Francisco)	Develops navigation and location-based services. Their software is used by a variety of companies such as; Uber, Ford, and Hyundai.
44. TESLA (2003)	California (Palo Alto)	According to the CEO, it will achieve full autonomy by 2023. Tesla offers the most range of any EV on the market. They are also among the most secure in the world. They are also a lot of fun to drive. L4-Autonomy.
45. TOYOTA (1937)	Fully remote	Toyota is using its automated driving technology to develop new mobility solutions, such as robots with increased vision, reasoning, and manipulation that can provide extended freedom of movement for all, including persons with limited mobility.
46. UNITY (2004)	California (San Francisco)	It is the world's top real-time 3D rendering tool for game development and other interactive content creation. In AV, key features are scripting flexibility, speed, rich interactivity, high end graphics, etc.
47. VALEO NORTH AMERICA, INC.	France (Paris)	Develops and manufactures several automotive products, including lighting, powertrain, and thermal systems. Valeo is also developing AI and autonomous driving technology.
48. VINFAST LLC	Vietnam (Hanoi)	It's a member of Vingroup, the largest private corporation in Vietnam. With in just 21 months of launching in Vietnam, they become number one car seller in all of their competing segments.
49. VUERON TECHNOLOGY USA, INC	South Korea (Seoul)	They are developing autonomous driving technology that will allow their cars to drive autonomously in urban areas. The company's sensors use lidar and other technologies to create a 3D map of the vehicle's environment.
50. WAYMO (2009)	California (Mountain view)	With great initiatives, it is going to illustrate 4^{th} level AV cars. Uses a various ML algorithm to power its self-driving cars, including CNNs, RNNs, and RL.
51. WeRide Corp DBA	China	Developer of autonomous vehicle software in Chinese. The software is designed to enable self-driving cars to navigate complex urban environments.
52. WITRICITY (2007)	Massachusetts (Watertown)	Automatic wireless charging for mobile robots, AGVs, and cordless tools and instruments, removing the need for complex docking procedures and time-consuming manual recharging and battery replacement.
53. WOVEN PLANET NORTH AMERICA, INC	California (Palo Alto)	They are working on a system that will allow their cars to drive autonomously on highways.
54. XMOTORS.AI, INC	California (Santa Clara)	It is a developer of autonomous vehicle hardware and software. The company's technology is designed to enable self-driving cars to operate in both urban and rural environments.
55. ZOOX INC (2014)	California (Foster City)	Applies robotaxis for transport on specific public route (between two main offices travelling up to 56.327 km/h). The company is developing a self-driving car that is designed to be bidirectional (it can drive both forward and reverse without the need to turn around).

a rigorous threat analysis and risk assessment approach based on mathematical modelling to detect cyber-physical risks to AV perception systems that are crucial for AV driving behaviour and complex intersections in their operational design area.

5.3.6. Legal and ethical considerations (Altunyaldiz 2020; Landini 2020; Poszler 2021)

A number of legal and ethical considerations need to be addressed before AVs can be widely deployed. For example, how should liability be determined in the event of an accident

Table 5. Comparable table based on different automated vehicle machine learning algorithms.

Algorithm	Task	Strengths	Weaknesses
Bayesian Inference (Ma et al. 2021; Riboni et al. 2022)	Object detection, classification, prediction, and decision making.	Can handle uncertainty in the data and, can be used to combine information from multiple sensors.	Can be computationally expensive.
Deep neural networks (DNNs) (Fingscheidt 2022)	Object detection, classification, tracking, perception, and prediction.	Highly accurate and efficient, can learn complex patterns from data.	Can be computationally expensive and, require large data sets to train.
DeepLabv3+ (Memon et al. 2022; Wang, He, and Ma 2023)	Semantic segmentation	Accurate and fast	Can be computationally expensive.
Faster R-CNN (Alam et al. 2023; Nguyen 2019)	Object detection	Accurate and fast	Can be computationally expensive.
High transform (Gupta 2018)	Lane detection	Simple and robust	Can be in accurate in complex scenes.
Kalman filter (Kim and Bang 2018; Vignarca, Arrigoni, and Sabbioni 2023)	Motion prediction	Simple and robust	Can be in accurate in complex scenes
Random Forests (Sruthi 2021)	Object detection, classification, and prediction.	Can handle high-dimensional data and is robust to outliers.	Can be less accurate than DNNs for complex tasks.
Reinforcement Learning (RL) (Pérez-Gil et al. 2022; Reda and Vásárhelyi 2023)	Decision making, and control	Can learn to perform tasks without explicit programing and, can adapt to changing environments.	Can be computationally expensive and, require large amounts of data to train.
Support Vector Machines (SVMs) (Feng, Yan, and Zhang 2022; Velmurugan and Mathumitha 2019)	Object detection, classification, and prediction.	Good for tasks with small datasets and, robust to outliers.	Can be computationally expensive for large datasets.

Table 6. Current autonomous vehicle driverless testing permitted companies, algorithms, challenges and gaps, and their vulnerability.

Companies	Current status	Machine learning algorithms used	Challenges and gaps in machine learning methods	Vulnerabilities in autonomous driving
Apollo Autonomous Driving USA LLC. (Cloud 2020)	Has a permit for both driverless and driver-assisted testing.	CNNs, RNNs, and RRT.	Can be biased, which can lead to unfair and discriminatory outcomes. It can be fooled by adversarial examples, which are carefully crafted inputs that are designed to cause the model to make incorrect predictions.	It can be hacked. Can be susceptible to noise in the data, which can lead to inaccurate predictions.
Autox Technologies Inc. (Xiao 2021)	Has a permit for both driverless and driver-assisted testing.	Lidar Point Cloud Segmentation	Requires a large amount of data to train, which can be expensive and time consuming to collect. It is complex and difficult to understand, which can make it difficult to debug and troubleshoot.	Can be poisoned by malicious actors who inject bad data into the training dataset. It can also overfit the training data, which can lead to poor performance on real-world data.
Nuro INC. (Nuro.ai)	Has a permit for both driverless and driver-assisted testing.	CNNs.	It can be computationally expensive to train and run. This model can be slow to adapt to new changes in the environment.	It can be confused with unexpected or rare events. Can be fooled by physical attacks, such as covering up traffic signs or projecting misleading images onto the road.
Waymo LLC. (Waymo 2022)	Has a permit for both driverless and driver-assisted testing.	CNNs, RNNS, and RL.	This model can be difficult to verify and validate. It can be opaque, which can make it difficult to understand how they make decisions.	It can be susceptible to cyberattacks. In addition, it can be fooled by adversarial examples.
Weride corp. (Weride)	Has permit for driverless testing.	CNNs, Mask R-CNN, RNNs, DeepLabv3+, LSTM, GRU, DQN, and RRT.	It is sensitive to changes in the environment, such as weather or lighting. Difficult to generalise to new environments.	It can be fooled by sensor spoofing, which is a technique in which an attacker sends false sensor data to the autonomous vehicle. It can be hacked to take control of the vehicle.
Zoox INC. (Inc)	Has a permit for driverless testing.	CNNs, LSTM, RNNs, and GANs,	It can also be slow to learn from new data. It is difficult to deploy at scale.	It can be fooled by adversarial examples. It can be susceptible to sensor noise.

involving an AV? How should AVs be programmed to make decisions in complex ethical situations?

5.3.7. System failures

Autonomous vehicles rely on complex software and hardware systems, and any failure in these systems could lead to an accident (Mishler and Chen 2023).

5.3.8. Human error

Even though autonomous vehicles are designed to operate without human input, there are still situations where human intervention may be necessary. If the human driver does not take appropriate action in these situations, an accident could occur (Mueller, Cicchino, and Zuby 2020).

5.3.9. Unforeseen circumstances

Autonomous vehicles are trained on large datasets of real-world data, but it is impossible to anticipate every possible situation that a vehicle may encounter on the road. This means that autonomous vehicles may not be able to respond appropriately to unforeseen circumstances, such as a sudden construction zone or pedestrian jaywalking. Despite these vulnerabilities, autonomous vehicles have the potential to revolutionise transportation. They can make roads safer and more efficient, and to provide new mobility options for people with disabilities and other underserved populations. As technology continues to develop and be tested, we can expect to see autonomous vehicles become increasingly common on our roads. Sample algorithms and their relevant configurations are shown in the Table 5 below.

These are only a small sample of the many machine learning algorithms that can be used for AVs. The best algorithm and configuration for a particular task will depend on a variety of factors, such as the specific requirement of the task, available computational resources, and developer expertise.

5.4. Current status of DMV autonomous vehicle driverless testing permitted companies with ML algorithms

The following (Table 6) shows summary of the current status of some of the DMV Autonomous Vehicle Driverless Testing permitted companies, with a focus on the challenges and gaps with machine learning methods and their vulnerabilities in autonomous driving.

According to (Nations 2019), a combination of different functions in particular are required to develop the functional performance of automated/autonomous vehicles. Of those functions for driving, minimum risk manoeuvre, transition demand, environmental monitoring (headway, side, rear), lateral control (i.e. lateral discipline), longitudinal control (acceleration, braking and road speed), transition demand, Human machine interface (HMI) both internal and external and Drive monitoring for applications. ISO (2018) defined functional safety as the absence of unreasonable risk due to any potential source of harm caused by malfunctioning behaviour of electrical and/or electronic systems. This means that a malfunctioning behaviour is not limited to failures but also includes unintended behaviour (with respect to design intents).

5.5. Principles of functional performance requirements

Hence, functional performance was the backbone for vehicle operations, guided by principles for fitness of ideas. A requirement that focusses on functional be a formal indicating 'shall statement' that specifies a task or activity carried out by an ITS unit. While saying this, wants to elaborate that each functional need is unique and discrete, specifying the tasks that an ITS system obliged to execute. This needs introductory comments like (Unec 2020) vehicle definitions and classifications, high level approach, operational domain, autonomy, accidents, free of unreasonable safety risks, disruption of the flow of normal traffic, destruction of property, and rational vs reasonable before knowing operational design domains, i.e. describes the operating conditions under which an ADS or feature thereof is specifically designed to function (Standard).

Operational design domain (Environmental conditions): weather, geolocation, road features, and manoeuvres. Machine operates based on the manufacturer's settings either editable by user or once set. To be productive, following the route set by producer should be enhanced per the agenda. Light, radio waves, forces, and sounds must be sensed as the first message from the ordered instrument and localised. The localised message could be perceived to predict the conditions next to that and adjust for planning. Hence, planning determines the order of all good or bad messages. The planned information based on predictions controlled for steering, brake, throttle, and commands that are tangibly applied. Figure 8 explains briefly as follows.

Figure 8 shows very basic AV functional architectures that have been elaborated in more detail (Badue et al. 2021; Yurtsever et al. 2020). Sense a various sensing modality. While map prior provides static map data and localises' to calculate position, orientation, and motion of vehicles, it will perceive to calculate drivable area and obstacle location and motions.

To estimate future motion of dynamic objects, it predicts the perceived information.

Later, plan the predicted information to calculate a desired trajectory for the vehicle and control it to execute the trajectory as steering, brake, and throttle commands for applications.

Software impacts the implementation of perceiving and controlling information in either positive or negative ways. Table 7 shares more information on functional performance as follows.

The table presents definitions and compiles dependability terms and concepts from the ECSE, IEEE, and ISO standards. The functional requirements of San Francisco Bay area regional ITS architecture was selected based on the area's ITS services. As a result, these requirements have been tailored to the specific stakeholders, inventory, and regional objectives (Bay Area 2022; Transportation 2023). The mandatory functional requirements include Archive Data Repository, Archive government reporting, archive online analysis and mining, archive situation data archival, BIAC Data Collection, Border Inspection, Border Inspection administration, and others.

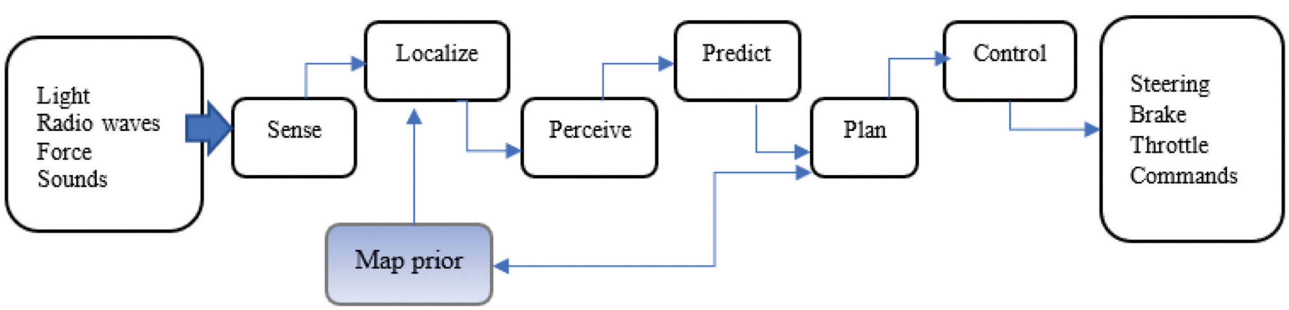

Figure 8. AV functional performance hierarchies.

Table 7. (SAE 2018) Reliability requirements, functions, and software information.

System reliability requirements	Its functions	Software functions for information
System prediction tolerance	Reliability models	Failure system component tolerance. Fault recovery tolerance. Error data component tolerance.
System maturity	Reliability assessment	Error handling input. Error in producing output. Error in producing correct output.
System fault tolerance		Fault prevention. Fault detection. Fault removal.
System recoverability		Failure operation. Failure mechanism.

5.6. Operational requirements

The ITS operational concept is a stakeholder-focused approach to ITS operational features.

While the service packages depict the flow of information between ITS elements to fulfil activities, the operational model explains the roles and duties of stakeholders in establishing, running and maintaining the regions' ITS. Each stakeholder's tasks and obligations are defined in the operational concept. These are associated with the implementation and operation of ITS. The operational concept describes what each stakeholder is required to do on a managerial and operational level in order to fulfil some area stakeholder's current and prospective roles and responsibilities. While operational safety is enhanced, operational requirements succeed. There should be a universal approach as on Figure 9, for the evaluation of AV safety, as shown below.

Figure 9 explains, operational safety as a result of vehicle safety, functional safety, and cybersecurity for automated vehicles. *Vehicle safety* encompasses the physical vehicle itself, including its hardware and software (Nhtsa 2022; Wang et al. 2020). Ensures whether the vehicle is physically capable of safety operating in its environment. This includes components such as brakes, airbags, and tyres, as well as the software responsible for controlling the vehicle's systems. *Functional safety*, on the other hand, focuses on the safety of the vehicle's functions (Joseph 2021). This includes its ability to perceive its surroundings and make informed decisions which are safe and appropriate. It involves elements like sensors, cameras, and algorithms that enable the vehicle to understand its environment. *Cybersecurity*, the third crucial factor, involves protecting the vehicle's systems from cyberattacks (Kim et al. 2021). This encompasses measures such as firewalls, intrusion detection systems, and secure coding practices. All three of these factors play vital role in ensuring the operational safety of automated vehicles. If any of these factors are compromised, it could result in a safety-critical incident.

6. Conclusions

Autonomous vehicles are currently the focus of research in today's world. Researchers and scientists are working on sustainable systems for the environment, which has gained acceptance from manufacturers and societies. According to researchers, automated driving systems (ADSs) promise a safe, comfortable, and efficient driving experience. However, users are still not fully ready to accept this system. Unfortunately, the number accidents involving vehicles equipped ADSs is increasing, as seen in daily and monthly reports. The lack machine learning algorithms is the main

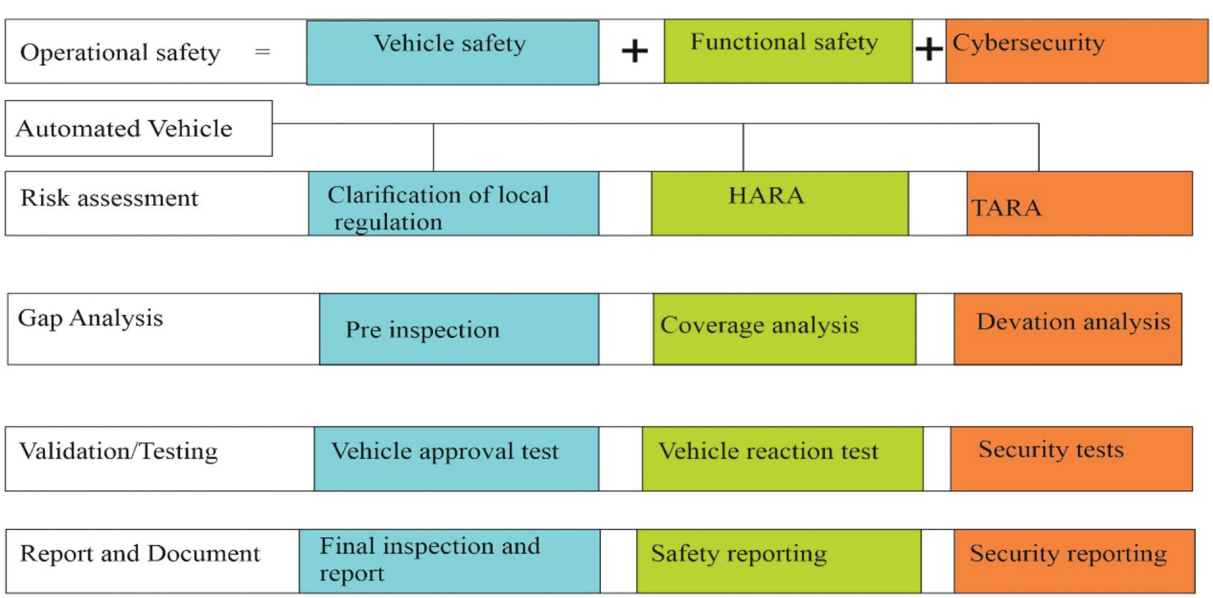

Figure 9. Overall approach for evaluation of AV safety.

reason for environmental perception. Until the state-of-the-art technology is strengthened and given more attention, the full potential of ADSs cannot be realised in our current reality. There is a lack of trust in societies when it comes to accepting driverless vehicles. Companies are transitioning from production to the trial/intern stage on their own roads. California is the city with the highest number companies manufacturing autonomous vehicles, and the California Department of Motor Vehicle reports every crash with automated vehicles on a daily basis. Statistical data collected from Science Direct was used for research conducted in 2010 and later to end of 2022. The research covered various disciplines such as health, computer science, environmental science, social science, decision science, and engineering. Graphical representations were used to analyse autonomous and automated vehicles separately, based on research articles, reviews, book chapters, encyclopaedias, and conference abstracts. The utilisation levels of different companies were identified based on abstracts, with Tesla, Waymo (Google), and Cruise being the most prominent in autonomous vehicle production and system investigations. Based on the reviewed research papers, articles, and conference papers, the researchers conclude:

(a) From a statistical point, it has been observed that the state of the art for automated vehicle related research slowly increasing since 2010, while autonomous vehicles started to rise in 2011 across all disciplines. On the other hand, in engineering (only) disciplines, research on automated vehicles is increasing more than autonomous driving vehicles.
(b) All operations of autonomous/automated vehicles depend on algorithms to perceive the environment. Therefore, machine learning algorithms should be improved to reduce the risk of crashes.

6.1. Future works for researcher

Hence, research related to automated and autonomous vehicles is currently underway, but there may be some deficiencies in the field. Therefore, future researchers should focus on the following areas:

(1) Investigating the shortcomings of algorithms used in automated and autonomous vehicles to improve the overall research on this AI system.
(2) Conducting research specifically on companies that offer software and system related packages to identify and review their capabilities.
(3) Developing enhanced algorithms to reduce vehicle accidents and comparing them with existing systems.
(4) Identifying the algorithms used by each autonomous vehicle company and assessing their reliability to ensure the production of error free and safe vehicles. Additionally, it is important to consider cost and consumer preference when studying the adoption of automated and autonomous vehicles.

List of abbreviations

ADS	Automated Driving System
AV	Automated Vehicle
AVs	Autonomous Vehicles
BASE	Bifield Academic Search Engine
CAVs	Connected and Automated Vehicles
CNNs	Convolutional Neural Networks
DNA	Deoxyribonucleic Acid
DQN	Deep Q-Network
GANs	Generative Adversarial Networks
GRU	Gated Recurrent Unit
HARA	Hazard Analysis and Risk Assessment
LSTM	Long short-term memory
R-CNNs	Region based Convolutional Neural Network
RNNs	Recurrent neural networks (RNNs)
RL	Reinforcement Learning
RNNs	Reinforced Neural Networks
SAE	Society of American Engineers
SAGE	Open access, peer-reviewed, academic mega journal
TARA	Threat Analysis and Risk Assessment
UK	United Kingdom
US	United States

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Data availability statement

We can encourage that the data we have used in this paper are available on our hands and we can be ready to provide when necessary.

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