Systematic Literature Review on Autonomous Vehicles

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Abstract

This systematic review provides a comprehensive analysis of 56 articles published between 2017 and 2023 on vehicle autonomy frameworks. The review categorizes autonomous vehicles into different levels of autonomy and examines the associated features, aiming to simplify and clarify the field. The gradual progression from manual control to full automation is explored, with advancements discussed at each level, including driver assistance features, semi-autonomous capabilities, conditional driving automation, high automation, and full automation. The review also highlights the importance of sensor integration, software modularity, and real-time decision-making for achieving Level 5 autonomy. Furthermore, the review emphasizes the significance of trust, safety, and security in the adoption of autonomous vehicles, taking into account factors such as operating conditions and user experiences. By identifying gaps in the existing literature, the review identifies areas that require further research. It emphasizes the integration of advanced technologies, meticulous safety considerations, and a focus on enhancing the user experience as crucial elements for the development and widespread acceptance of autonomous vehicles.
Keywords: *Autonomous vehicle , path mapping , sensors , detection , level of autonomy ,automatic parking*

1 Introduction

In a world where technology is developing at an unprecedented pace, one innovation stands out as a potential game-changer for transportation: autonomous vehicles." Autonomous vehicles (AVs) are capable of sensing their environments and navigating different traffic conditions with little or no human input((Skeete, 2018). Driverless cars and other AVs are said to have the potential of changing transportation for the better. These self-driving cars and AVs are capable of making driving easier and allow greater mobility than ever before.

Autonomous vehicles can be used by a wide range of individuals such as people who drive a lot and want to utilize their time, or people who are unable to drive due to health issues.

Autonomous vehicles are essential because they can improve safety, reduce traffic jams, save lives, reduce congestion, and increase accessibility for individuals who are unable to drive.

The evolution of autonomous vehicles has widely significant progress over the years. The early concept of autonomous vehicles began in the 1920s when the first driverless car was created. In 1950, the first automated guidance systems were developed for experimental purposes. In the 1980s The Defense Advanced Research Projects Agency (DARPA) initiated research projects to develop autonomous vehicles for military applications. Between the1990s-2000s there was an impressive development of Advanced Driver Assistance Systems (ADAS). ADAS technologies such as adaptive cruise control, lane-keeping assistance, and automatic braking systems started to appear in production vehicles. In the 2010s, there was significant progress toward fully autonomous vehicles. Companies like Google (now Waymo) and traditional automakers started testing self-driving car prototypes on public roads. Growing Industry and Regulatory Focus (2010s-2020s) Google, Tesla Motors, and several other automobile companies envision a future with reduced traffic problems, fewer road accidents, and a more efficient public and private transport system starting in 2020.

The categories of autonomous vehicles: Level 0 (No Automation) : The vehicle is controlled by the human with no assistance from an automation system. all aspects of driving such as steering, braking system, and acceleration are manually controlled by the driver. Level 1(Driver assistance): in this level the system provides specific driver assistance function, example : adaptive cruise control , lane control, and steering. Level 2 (Partial automation) : in this level capable of taking control of some system such as steering and accelerating. Level 3(Conditional driving automation) : there are capabilities and can make decisions for themselves and analyze the environment and use sensor to record what happens , but require human override. Level 4(High automation) : highly autonomous can perform most driving tasks without human interaction and use AI algorithms. Level 5 (Fully automation) : can perform all tasks under all conditions , no need for human control.

Autonomous vehicles Advantages: Provide independent transportation: Autonomous vehicles offer self- reliant transportation for people who for any reason are unable to drive or shouldn't drive, which is directly advantageous for those travelers, by enhancing the ability to reach their educational and employment opportunities, can increase their productivity. Utilize the journey time: Even with the development in vehicle technology and driver assistance systems, the driver must still concentrate on driving 100% of the time. However, the advent of highly and fully automated vehicles will change this by enabling drivers to utilize their travel time for various activities such as: reading a book, surfing the web, watching films, etc. Improving safety: More than 90% of collisions are by human error, including failing to look properly, being impatience, easily distracted. In contrast, automated vehicles are equipped with a variety of sensors, which will constantly monitor their surroundings.

Autonomous vehicles disadvantage: Technical limitations: Poor weather conditions have the potential to impact sensors, decrease visibility, and obstruct GPS signals, potentially leading to car accidents or causing delays in deliveries. Job displacement: The widespread adoption of autonomous delivery vehicles has the potential to result in job displacement for human drivers[27].

The difference from the other reviews is that our study conducts a systematic review of the literature spanning from 2017 to 2023, specifically focusing on frameworks that analyze the different levels of autonomy in vehicles. This unique approach sets our review apart from others, as it provides an up-to-date and comprehensive analysis based on recent studies.

Research Questions

The following research questions are addressed in this systematic literature review:

- How has the evolution of autonomous vehicle technology progressed across different levels of autonomy from 2017 to 2023?
- How has the functionality and capability of Level 0 (No automation) vehicles evolved over the period from 2017 to 2023?
- What advancements characterize the progression of Level 1 (Driver assistance) autonomous vehicle technologies during the specified timeframe?
- What notable features and technologies define the evolution of Level 4 (High Automation) autonomous vehicles between 2017 and 2023?
- To what extent has Level 5 (Full automation) autonomy been achieved, and what challenges persist in realizing fully autonomous vehicles?

2 Literature Review

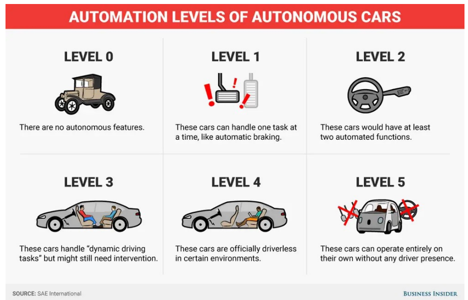

Figure 1: Levels of Autonomous Vehicles

Autonomous vehicles have emerged as a transformative technology in the transportation industry. As these vehicles continue to evolve, it becomes crucial to develop systematic frameworks for evaluating their performance and capabilities at different levels of autonomy. This literature review aims to analyze and discuss the criteria associated with each level of autonomy in an autonomous vehicle, as outlined in the provided framework.

2.1 Level 0: Emergency Braking System and Airbag

Paper [5]: provides a systematic analysis and research on the impact factors, key technologies, and effect evaluation of Autonomous Emergency Braking (AEB) systems. The authors extensively analyze three levels of factors influencing AEB performance, including vehicle factors, driver factors, and environmental factors. They further investigate the technical status of environment perception, decision-making, and control execution subsystems. The performance of AEB systems from Mazda, Honda, NHTSA, Berkeley, and Seungwuk Moon is compared and analyzed based on MATLAB simulations. The paper also summarizes current AEB virtual test methods, closed-field test methods, and test sites. Additionally, it examines three classic evaluation methods, namely AEB test evaluation standards of ENCAP, IIHS, and i-Vista. Based on the findings of Paper [5], it is evident that the effectiveness of the AEB function relies on the appropriate selection of potential targets at risk and timely execution feedback. The perception ability of driving environment information plays a crucial role in restricting the development of automatic emergency braking systems. Sensor fusion combined with vehicle-to-everything (V2X) communications is proposed as a means to enhance the application and sensing range of AEB systems. Moreover, the paper highlights the need for studying AEB collision avoidance strategies in complex multitraffic scenarios to optimize their comprehensive performance. It also suggests the use of augmented reality or mixed reality methods to reconstruct, configure, and enhance cost-effective test scenarios.

Additionally, **Paper [6]:** focuses on the development of an Autonomous Emergency Braking System (AEBS) that can autonomously identify potential forward collisions and activate the vehicle braking system. The paper proposes a sensor fusion approach using lidar, radar, and vision sensors to improve the efficiency and reliability of the AEBS. Simulation experiments conducted in a MATLAB/Simulink environment demonstrate the stable operation of the AEBS in avoiding forward collisions, even in the presence of measurement errors in any one sensor. The study highlights the importance of scalable, reliable, secure, fault-tolerant, and interoperable technologies in supporting AEBS. Moving on to the airbag system in autonomous vehicles,

Paper [7]: emphasizes the need to adapt airbag designs to ensure occupant safety, considering that autonomous vehicles allow for occupants seated in non-standard positions. The authors propose an airbag design suitable for both assisted and autonomous driving conditions, with a focus on the driver's airbag. The study employs a Design of Experiments (DoE) methodology and experimental tests to select airbag geometry, threads, seam strength, and seam geometries. An adaptive system based on sewn tethers is proposed to allow the airbag to adapt to different driving modes. Experimental validation confirms the expected behavior of the airbag design, indicating its capability to protect drivers in vehicles capable of autonomous driving. The research in Level 0 autonomous vehicles highlights the importance of effective emergency braking systems (AEB) and airbag designs. The evaluation and integration of key technologies, such as sensor fusion and adaptive systems, play a crucial role in enhancing the performance and reliability of these safety features. The cited papers [5], [6], and [7] provide valuable insights into the evaluation and development of emergency braking systems and airbags in Level 0 autonomous vehicles. They analyze the impact factors, technical status, evaluation methods, and propose future research directions. The studies contribute to the understanding of AEB performance, sensor fusion, and adaptive airbag designs. The findings from these papers can be integrated into the broader context of evaluating and improving safety systems in autonomous vehicles. By considering factors such as vehicle, driver, and environmental influences on AEB performance, as well as the use of sensor fusion and adaptive airbag systems, researchers and engineers can work towards enhancing the safety and reliability of Level 0 autonomous vehicles. The papers emphasize the need for comprehensive evaluation methods, including parameters such as time-to-collision, peak value of braking deceleration, and success rates of sensor recognition and collision avoidance. They also highlight the importance of studying collision avoidance strategies in complex scenarios and the impact of AEB systems on overall traffic efficiency. Additionally, the proposed airbag design focuses on adapting to different driving modes and ensuring occupant safety in non-standard seating positions.

2.2 Level 1: Adaptive Cruise Control, Steering, Lane Control, Gear

Adaptive Cruise Control (ACC) is an advanced driver assistance system that enables vehicles to maintain a safe distance from the preceding vehicle by automatically adjusting speed and acceleration. This section focuses on the evaluation of ACC systems, as well as steering, lane control, and gear systems, and their impact on traffic flow efficiency, capacity, and queue discharge rate. A study conducted by [1] aimed to assess the impact of ACC on traffic flow efficiency through a naturalistic driving study. The study involved eight participants driving ACC-equipped vehicles on freeways for 4 to 5 weeks. Data on spacing, headway, speed, acceleration, lane use, and the number of lane changes were collected and compared between ACC On and ACC Off in different traffic states.

The findings regarding ACC have already been discussed in the earlier section. However, the evaluation of steering, lane control, and gear systems specifically related to their impact on traffic flow efficiency requires further research and review of relevant literature. The provided papers [3] and [2] primarily focus on the control strategies, safety aspects, and overall architecture of steering and autonomous vehicle systems rather than specifically evaluating their impact on traffic flow efficiency. While the evaluation of ACC systems has shown positive effects on traffic flow efficiency, the specific evaluation of steering, lane control, and gear systems' impact on traffic flow efficiency requires additional research. It is important to understand how these systems interact and integrate with ACC to collectively enhance traffic flow efficiency.

Given the limited information available in the provided papers [3] and [2], further research and review of relevant literature are necessary to comprehensively address the impact of steering, lane control, and gear systems on traffic flow efficiency in the systematic review paper. These aspects should be explored to gain a comprehensive understanding of the overall impact of these systems on traffic flow.

In conclusion, while the evaluation of ACC systems has provided valuable insights into their effects on traffic flow efficiency, additional research is required to comprehensively address the impact of steering, lane control, and gear systems. Future studies should focus on evaluating the integration and collective impact of these systems to optimize traffic flow efficiency.

2.3 Level 2: Advancements and Challenges in Autonomous Vehicle Technologies

Autonomous vehicles have gained significant attention in recent years, with major automotive companies announcing their plans to introduce driving automation modes in the 2020s. This technology holds the promise of safer and more efficient transportation, improved accessibility, comfort, convenience, and environmental friendliness. However, it also raises controversies, especially in light of recent deadly accidents. In this literature review, we explore the ad-

vancements and challenges in autonomous vehicle technologies, focusing on path planning algorithms and techniques [11]
One crucial aspect of autonomous vehicles is motion planning, which involves path generation and decision making. Highway driving presents specific challenges, including high speeds, small curvature roads, and adherence to driver rules within a constrained environment framework. Lane change, obstacle avoidance, car following, and merging are some of the critical situations addressed in the literature. Several algorithms have been developed and reviewed, each with its unique features and applications in highway driving scenarios. Autonomous surface vehicles, particularly those operating at sea, are also gaining attention due to their potential benefits in terms of safety and efficiency. Path planning algorithms for these vehicles aim to reduce the risk of collisions, groundings, and stranding accidents. The literature review focuses on the guidance, regulatory framework, navigation, and control components specific to autonomous surface vehicles. It also examines the classification and terminology used in the field, with an attempt to clarify ambiguities associated with path planning [12]
A lane-level map is an essential component of autonomous driving, and generating a lane-level road network is a fundamental step in creating such maps. Various research efforts have been dedicated to developing techniques for lane-level road network generation using onboard systems. This literature review provides an overview of the methods used for data collection, lane-level road geometry extraction, mathematical modeling, and representation of the road network. The advantages, limitations, and summaries of these techniques are analyzed and discussed [13]
Accurate localization and mapping are crucial for autonomous vehicles to navigate their environment effectively. The review highlights the localization and mapping requirements for different levels of autonomy, ranging from driver assistance features to fully autonomous operations. It examines the system decomposition, redundancy, and positioning requirements necessary to achieve the desired level of safety. Representative autonomous and assistance features are discussed, and recommendations are made regarding map georeferencing and information integrity [14]
improving localization accuracy in autonomous vehicles using a stereo camera sensor and the ORB-SLAM 2 package. The authors first build and save a map of visual features at low speeds, then reload and localize on the saved map in subsequent runs. The approach enhances localization accuracy and reduces computational load compared to full SLAM. The authors evaluate the method using the KITTI dataset and their small-scale electric model car, showing a translation error below 1% in a feature-rich environment [15]
A novel approach to localization in urban environments involves utilizing aerial imagery maps and LIDAR-based ground reflectivity. Traditional techniques rely on high-definition reflectivity maps, which can be costly and labor-intensive to maintain. This literature review explores a method that uses aerial/satellite imagery to provide real-time localization performance comparable to state-of-the-art LIDAR-based maps but at reduced costs. The technique is evaluated using a real-world dataset collected from a test track, demonstrating its potential for

autonomous vehicles in urban environments [development of autonomous vehicle technologies and the advancements in path planning algorithms and techniques. It emphasizes the importance of motion planning, path generation, and decision making in highway and surface driving scenarios. The generation of lane-level road networks, localization, and mapping techniques are also critical for enabling safe and efficient autonomous navigation. The incorporation of aerial imagery and LIDAR-based reflectivity maps shows promise in reducing costs while maintaining accurate localization. Further research is needed to address the challenges, evaluate the performance in complex scenarios, and develop new regulations for autonomous vehicles [16][17]

2.4 Level 3: Conditionally Automated Driving

To improve vehicle safety and allow autonomous operation, advanced driver assistance systems (ADAS) and autonomous driving mainly rely on a combination of sensors. These sensors, which each have a specialized function in the perception and detection of the vehicle's surroundings, include stereo cameras, infrared (IR) cameras, LiDAR systems, radar systems, and ultrasonic sensors [23]. Applications like obstacle detection and traffic sign recognition benefit from the 3D information provided by stereo cameras. Thermal radiation is captured by infrared cameras, which are widely employed in night vision applications [24]. While radar systems use microwaves to estimate speed and distance and are not impacted by bad weather, LiDAR systems use laser beams to calculate object distances and produce detailed 3D images [22]. Sound waves are used by ultrasonic sensors to detect proximity [24].
Sensor fusion, which combines data from several sensors, is essential to enhancing the accuracy and dependability of ADAS functions. This fusion makes up for the shortcomings of individual sensors and enables a more thorough understanding of the surroundings. Conventional methods for sensor fusion include Bayesian estimation and Kalman filtering, which are classical algorithms based on uncertainty theories [23]. But deep learning-based algorithms are also being used for sensor fusion, making use of artificial neural networks' ability to extract valuable information from sensor data [26].
However, addressing the security flaws associated with these sensors is critical. Vulnerabilities in ultrasonic sensors, in particular, have been identified, posing potential threats to autonomous driving. Physical signal level attacks, such as spoofing and jamming, can manipulate ultrasonic sensor output, leading to incorrect driving decisions. Defense strategies such as Physical Shift Authentication (PSA) and Consistency Check (MSCC) have been proposed to improve sensor reliability and authentication to mitigate these risks [25].
The integration of experimental platforms is critical in the context of autonomous driving education. Mobile phones have been investigated as experimental platforms for integration, allowing students to implement and test various autonomous driving tasks such as localization and obstacle detection. This modular and integrated approach divides the complex system into technology modules, giving students a thorough understanding of autonomous driving [34].

In autonomous driving, the control model includes the planning and control subsystems that are in charge of making decisions and carrying out actions [35]. Students can use the integration experimental platform to implement and test planning and control functions, learning how different modules interact and contribute to the overall control of an autonomous vehicle [34].
In addition, LiDAR and radar sensors are widely used in ADAS for collision avoidance, adaptive cruise control, and blind-spot detection. LiDAR technology uses laser pulses to measure distances and create a 3D representation of the environment, whereas radar technology detects and tracks targets using electromagnetic waves. Sensor fusion combining LiDAR, radar, and cameras is critical for autonomous systems [22].
In summary, essential components of the literature on ADAS and autonomous driving include the integration of multiple sensors, sensor fusion techniques, security flaws, experimental platforms, and the control model. Overcoming security issues, improving sensor dependability, and offering thorough instruction and comprehension are essential for the effective adoption and development of autonomous driving technologies.

2.5 Level 4

2.5.1 Computer Vision

Autonomous vehicles (AVs) are becoming crucial assets, attracting attention for both civilian and military applications [27]. Recent developments in advanced control, perception, and motion planning techniques are surveyed, emphasizing the need for sensor fusion, computer vision, system identification, and fault tolerance [27]. The survey outlines the practical issues and technical challenges associated with autonomous vehicle development, setting the stage for future research [27]. The demand for AVs is on the rise, with applications spanning inspection, surveillance, and rescue operations in military settings [27].
Sensor fusion is pivotal for AVs, with the choice of estimation technique dependent on the problem and assumptions made [27]. Computer vision, especially utilizing cameras, presents a promising yet challenging approach for AVs across diverse environments [27]. Future planning involves hybrid positioning techniques for improved GPS/INS integration [27]. Fault tolerance controls are crucial to prevent faults from escalating, enhancing system reliability and reducing unforeseen hazards [27]. System identification aids in evaluating system dynamics, contributing to safer and more reliable AVs [27].
In the realm of intelligent transportation systems (ITS) and autonomous driving (AD), computer vision has shifted towards deep neural network architectures [29]. Despite performance improvements on benchmark datasets, real-world challenges persist, including data issues, model complexities, and urban environmental complexities [29]. Challenges include data collection and labeling, model processing on embedded hardware, and issues related to irregular lighting and occlusions in complex urban settings [29].
The evolution of image recognition has seen a shift to deep learning, significantly

impacting ITS and AD [30]. The paper outlines the application of deep learning in image recognition tasks, emphasizing the need for end-to-end learning and reinforcement learning for judgment and control in autonomous vehicles [30]. Challenges include justifying outputs and transitioning from visual to verbal explanations through natural language processing [30].
AVs, while holding the potential to solve traffic problems, face challenges in accurately perceiving their environment for safe navigation [31]. The review focuses on computer vision techniques for AV perception systems, emphasizing the detection of pedestrians and vehicles [31]. Both traditional and deep learning techniques have been employed, with DL showing superior results [31]. Challenges include detecting small, occluded objects and improving performance in adverse conditions [31]. The need for testing on challenging datasets is highlighted to overcome limitations in existing datasets [31].
In summary, these literature reviews provide a comprehensive overview of the advancements and challenges in autonomous vehicles and computer vision. From sensor fusion to fault tolerance, and deep learning applications to challenges in computer vision for AV perception systems, the papers collectively contribute valuable insights, setting the stage for future research directions in these dynamic fields.

2.5.2 perception:

In recent years, the surge in autonomous vehicle technologies has introduced challenges, notably in handover processes requiring constant human supervision. A critical aspect lies in appropriate handover modeling for safety, as outlined in a literature review that unifies psychological and physiological control theory models, emphasizing the need for a comprehensive understanding of situation awareness (SA) and its integration into control-oriented human driver models for effective simulations and performance measures [38]. Concurrently, user acceptance of autonomous vehicles has become a pivotal focus, extending beyond technical concerns to sociodemographic characteristics. A comprehensive survey identifies diverse attitudes influenced by age, education, and gender, emphasizing the necessity of a multi-perspective approach for future research and highlighting the importance of real interactions between users and autonomous vehicles [39]. Furthermore, the societal acceptance of autonomous vehicles is intrinsically tied to their explainability. An in-depth examination underscores the significance of transparent and trustworthy systems, advocating for interdisciplinary research and proposing a conceptual framework for explainable autonomous driving [40]. Lastly, public perceptions play a pivotal role, particularly among vulnerable road users, with direct interaction experiences shaping positive attitudes and expectations regarding safety benefits. The study recommends policymakers facilitate interactive experiences with autonomous vehicles to foster wider public acceptance and integration of this transformative technology [41].

2.5.3 Human-Machine Interface (HMI):

The acceptance of autonomous driving remains a challenge, prompting an analysis of Human-Machine Interfaces (HMIs) and user acceptance of Autonomous Vehicles (AVs). The literature review covers changes in user interaction with AVs, emphasizing the impact of internal and external HMIs on user behavior, experience, and acceptance models. It identifies research gaps and emphasizes the importance of human-centered AV design to enhance user trust and acceptance [42]. Connected autonomous vehicles (CAVs) offer increased mobility, especially for older adults, and this paper proposes an emerging framework for in-vehicle CAV HMIs, particularly for those aged 70 and above. The review highlights principles in accessibility, usability, functionality, and adaptability, emphasizing the importance of experience, training, and individualized solutions. It addresses a critical gap in the literature on AV and CAV HMI design principles for older adults and advocates for concentrated research to inform effective HMI design [43]. Teleoperation of vehicles emerges as a solution for utilizing automated driving benefits when fully automated vehicles are not entirely feasible. The development of a user-centered HMI for teleoperation involves a systematic analysis of scenarios, resulting in a prototype evaluated for usability, situation awareness, acceptance, and perceived workload. Results support the effectiveness of the HMI design, with high satisfaction regarding interaction design and camera image presentation, providing valuable insights for further refinement and research [44].

2.6 Level 5: Adaptability and Passenger Experience

Autonomous vehicle technologies (AVTs) have been extensively researched and developed, but there is limited research on their adaptability to real traffic scenarios. Two papers contribute valuable insights on this topic. Paper [36] focuses on the adaptability of AVTs to Chinese cut-in scenarios, while Paper [37] explores the adaptability of autonomous vehicles in urban environments and analyzes their demands on infrastructure. Additionally, Paper [19] investigates the passenger/user experience of autonomous buses in a residential area of Oslo, Norway. Paper [36] presents a comprehensive analysis of Chinese cut-in scenarios using a large natural driving database. The authors extract and analyze over 3,000 cut-in scenarios to identify the technical requirements for AVTs in terms of perception, intelligent networking, and motion planning. Their comparative analysis reveals that current AVTs struggle to fully adapt to Chinese cut-in scenarios, highlighting unresolved challenges.

In Paper [37], the authors assess the adaptability of urban infrastructure for autonomous vehicles. They propose three standard models to evaluate the suitability of roads and networks based on the level of automation. The study compares three geographical locations and concludes that the adaptability of autonomous technology varies depending on the urban morphology and road network. The analysis suggests that grid-pattern cities are more suitable for autonomous vehicles, while organically grown cities with curvy narrow roads face greater challenges. Paper [19] addresses the user/passenger experience of autonomous buses in a residential area of Oslo. The study employs a mixed-methods approach to gather survey and interview data. Results indicate that passengers had positive intentions to use autonomous buses both before and after their introduction. Most users felt safe during their journeys, although they provided suggestions for improvement, such as increasing speed and reducing abrupt braking. Collectively, these papers shed light on the adaptability and passenger/user experience of level 5 autonomous vehicles. Paper [36] emphasizes the challenges of adapting AVTs to specific traffic scenarios, while Paper [37] highlights the importance of considering urban infrastructure and road networks. Additionally, Paper [19] provides insights into passengers' perceptions and intentions to use autonomous buses, offering valuable input for future deployments. While the studies discussed in this literature review provide valuable insights, it is important to note that the findings are context-specific and may not be directly applicable to other regions or scenarios. Further research is needed to explore the adaptability and passenger/user experience of level 5 autonomous vehicles in diverse contexts, considering factors such as cultural differences, regulatory frameworks, and technological advancements. In conclusion, understanding the adaptability of AVTs to real traffic scenarios and assessing the passenger/user experience are crucial for the successful deployment of level 5 autonomous vehicles. The findings from these papers contribute to the ongoing research in this field and provide valuable guidance for policymakers, motor corporations, and researchers involved in the development and implementation of autonomous vehicle technologies.

This literature review presented a systematic framework for evaluating autonomous vehicles at different levels of autonomy. Each level builds upon the previous one, introducing additional criteria and capabilities. At Level 4, the framework evaluates vehicles with high automation. These vehicles can perform all driving tasks under specific conditions and environments, allowing the human driver to disengage from the driving task and become a passive passenger. However, the driver must still be prepared to take control if the system requests or if the conditions exceed the vehicle's capabilities. Finally, at Level 5, the framework assesses fully autonomous vehicles that can perform all driving tasks under any conditions and environments. These vehicles do not require human intervention and enable passengers to engage in non-driving activities during the journey.

In addition to evaluating the capabilities of the autonomous vehicle at each level, the systematic framework considers various criteria that incorporate the framework to provide a holistic assessment of autonomous vehicles across different levels of autonomy.

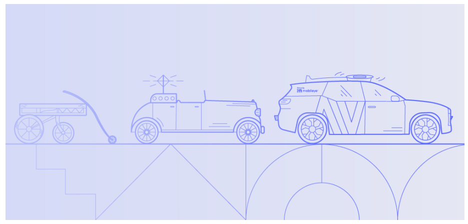

Figure 2: Evolution of Autonomous Vehicles

Overview

Goals: Through a meticulous exploration of the literature, the review seeks to provide a comprehensive and understandable analysis of autonomous vehicles and their levels of autonomy, the review will simplify and clarify the main concepts in the field related to autonomous vehicles. Additionally, it will identify gaps in the literature, highlighting areas where it was not discussed in the previous framework.
Aims: In light of the accelerating progress in the field of autonomous vehicles, this systematic review is to simplify the existing literature and define the areas with more and fewer publications in the field of autonomous vehicles. By categorizing and examining the existing research and developing an old framework to yield a thorough understanding of the current state of autonomous vehicles and their level of autonomy.
Objectives: After forming our framework we searched for the criteria belonging to each level of autonomy which simplified the way to conduct the systematic review, doing that we have reached our objective of simplifying the flow of how each level of autonomy is distinct by its own criteria yet is an extension of the next level and its criteria. In which we were able to investigate the contemporary landscape of autonomous vehicle research and its level of autonomy. Furthermore, the review was aimed to address key research questions, providing clarity on the existing knowledge base. Importantly, the paper endeavors to construct a robust framework that will assist researchers in building upon studies related to autonomous vehicles levels.
Paper Description

This systematic review embarks on meticulous scrutiny of the expansive literature encompassing autonomous vehicles. Employing a robust methodology, our approach involves a comprehensive search and selection process, meticulously curating relevant studies that significantly contribute to advancing our understanding of autonomous vehicle technology and its varying levels of autonomy. Moreover, The paper is composed of five main sections as follows, the first section is the introduction, the second section is a literature review, the third section is a framework, the fourth section is methodology, last section is the result and conclusion.

3 Framework

3.1 The Old Framework

The old framework consists of several interconnected stages:

The first stage:

Perception: The initial stage of the autonomous vehicle (AV) involves the use of various sensors to sense the surrounding environment and determine the AV's own position relative to its surroundings. Commonly employed sensors include RADAR, LIDAR, cameras, and more. The data collected by these sensors is then processed by recognition modules. The processed information from these modules is fused and passed on to the decision and planning stage.

In second stage (the decision and planning stage):

Decision and Planning: Building upon the perception stage, the decision and planning stage utilizes the gathered sensor data to make informed decisions, plan routes, and control the motion and behavior of the AV. This stage can be likened to the brain of the AV, as it performs tasks such as path planning, action prediction, and obstacle avoidance.

The control module, which follows the decision and planning stage:

Control: The control module receives the output from the decision and planning stage and is responsible for executing physical control actions on the AV. This includes functions like steering, braking, and acceleration, among others.

Finally, the chassis stage involves the interface between the AV's control module and the mechanical components mounted on the chassis. These components may include motors for the accelerator pedal, brake pedal, steering wheel, and gear mechanism. The control module signals and controls these components to carry out the desired actions.

3.2 Integration of the old framework:

To enhance and refine the existing framework for autonomous vehicles, we will focus on making it clearer and more efficient by adding the levels of autonomy which will make the stages more interconnected and more clear, where it involves:

- Chassis: The chassis refers to the physical structure of the vehicle. Within this framework, the chassis is mentioned in relation to the interface with various mechanical components.

- Level 0: Level 0 represents the lowest level of automation in the framework. It includes basic safety features such as the emergency braking system and airbags.

- Level 1: Level 1 introduces some automated functions, including adaptive cruise control for accelerating, steering control, lane control, and gear shifting.

- Level 2: Level 2 introduces planning aspect that involves the integration of advanced driver assistance systems (ADAS) to simultaneously control steering and acceleration under specific conditions, in which we have: Decision Planning: This stage involves decision-making and planning processes for the AV. Path planning refers to determining the optimal route for the vehicle, while localization involves determining the AV's precise position.

- Level 3: The driving system has the capability to perform various functions, including sensing the environment to gather information about its surroundings and exerting control over the vehicle's actions, in which we have: Control: The control module receives input from the decision planning stage and is responsible for executing control actions. It encompasses the control modules necessary for operating the AV, in which we have:

  Perception: The perception stage focuses on sensing the AV's surroundings using various sensors. The mentioned sensors include ultrasonic sensors, cameras, LiDAR, GPS, and radar. These sensors provide data that is processed by recognition modules.

- Level 4:this level represents a substantial leap in the integration of recognition models in autonomous vehicles, in which a vehicle is capable of performing most driving tasks without human intervention within specific operational domains, in which we have: Recognition Modules: These modules, such as computer vision and image processing, analyze the data collected by the sensors and extract meaningful information about the environment.

- Level 5: This level is called "full automation" this term refers to the highest level of automation, where the AV is capable of performing all driving tasks without any human intervention. The framework mentions adaptability and passenger experience as aspects to consider in achieving full automation. Our framework provides a structured overview of the components and automation levels involved in autonomous vehicles where each level is a continuation of the next level and its criteria.

3.3 New conceptual framework

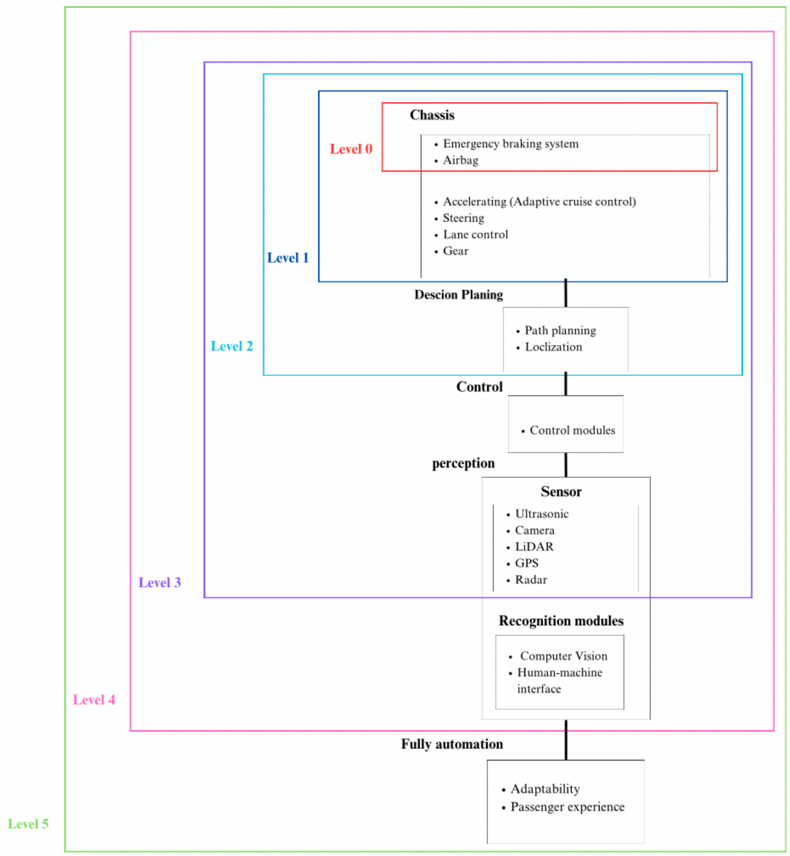

Figure 3: Framework

Description of each part and criteria

3.4 Level 0 (No automation)

Level 0 refers to the absence of any autonomous characteristics or support systems in the context of vehicle autonomy. At this level, the vehicle is entirely controlled by humans, with no automatic assistance. The driver is entirely responsible for all elements of driving, such as acceleration, braking, steering, and monitoring the surroundings. cars with Level 0 autonomy lack advanced sensors, algorithms, and decision-making skills seen in cars with greater degrees of autonomy. As a result, they, like traditional non-autonomous cars, rely exclusively on the driver's abilities and attention.

3.4.1 Emergency Braking System

Emergency braking system primarily relies on traditional braking technologies rather than autonomous intervention. These vehicles are equipped with conventional braking systems that operate based on driver input. When the driver applies the brakes, the system engages the mechanical components to slow down or stop the vehicle(U.S. Department of Transportation(2017)).

3.4.2 Airbag

An airbag is a car safety component that inflates quickly during a collision to form a cushioning barrier between people and harsh objects. It minimizes the impact pressures on occupants, resulting in fewer injuries. Airbags function in tandem with seat belts to give the best possible protection. (Franco, B., Alves Ribeiro, J. M., & Sánchez-Arce, I. D. J. (2023))

3.5 Level 1 (Driver assistance)

Level 1 serves as an introduction to vehicle automation, offering partial assistance in driving tasks while underlining the vital role of the driver in ensuring safe and efficient operation. The vehicle features a single automated system for driver assistance, such as steering or accelerating (cruise control). Adaptive cruise control, where the vehicle can be kept at a safe distance behind the next car, and each criterion represents an area where the vehicle provides specific levels of autonomy and assistance while ensuring the driver's continued involvement and oversight in the driving process at Level 1 autonomy.

3.5.1 Accelerating (Adaptive cruise control)

Adaptive Cruise Control (ACC) is an advanced driver assistance system that falls under the category of Level 1 autonomy in vehicle automation. This technology enhances the traditional cruise control by incorporating intelligent features that adapt to the dynamic flow of traffic, providing a more sophisticated and responsive driving experience. The primary function of Adaptive Cruise Control is to automatically adjust the vehicle's speed to maintain a safe following distance from the vehicle ahead. ACC utilizes sensors, radar, or cameras to monitor the road and the distance to the vehicle in front. This allows the system to modulate the speed of the vehicle, slowing down or accelerating as necessary to keep a safe and preset gap.(schakel, W. J., Gorter, C. M., De Winter, J. C., & Van Arem, B. (2017), Magdici, S.,& Althoff, M. (2017),h e, Y., Ciuffo, B., Zhou, Q., Makridis, M., Mattas, K., Li, J., ... & Xu, H. (2019)).

3.5.2 Steering

The steering component represents a critical aspect of driver assistance systems. At this level, the automated system primarily focuses on providing partial assistance in steering, emphasizing the continued involvement of the driver in

ensuring safe and effective control of the vehicle.
The steering assistance in Level 1 often takes the form of systems designed to ease the physical effort required for steering, making it more comfortable for the driver, especially in certain driving conditions. These systems may include Electric Power Steering (EPS) This maintains a crucial balance between automation and the driver's engagement, ensuring that the driver is ready to take over in case of unexpected situations or challenges on the road(Berntorp, K., Quirynen, R., & Di Cairano, S.(2019), Xiangkun He, Yulong Liu, Chen Lv, Xuewu Ji & Yahui LiuTo (2018))

3.5.3 Lane control

Lane control is a crucial aspect of Level 1 autonomy in vehicle automation, emphasizing the system's ability to assist the driver in maintaining the vehicle within its designated lane on the road. At this level, lane control typically involves technologies that provide support and guidance to the driver, promoting safer and more stable driving
One of the key features associated with lane control at Level 1 is Lane Keeping Assistance (LKA) or Lane Departure Warning (LDW) systems. These systems utilize sensors, cameras, or other detection mechanisms to monitor the vehicle's position within its lane. If the system detects an unintended departure from the lane without the use of turn signals, it can provide visual or audible warnings to alert the driver, encouraging prompt corrective action. (Chae, H., Jeong, Y., Lee, H., Park, J., & Yi, K. (2021), Hu, J., Xiong, S., Zha, J., & Fu, C. (2020))

3.5.4 Gear

The gear component primarily refers to the transmission system and the driver's control over the vehicle's gears. whether at Level 1 autonomy does not usually involve automated gear shifting. The driver retains full control over selecting and engaging gears. However, certain vehicles may have manual transmissions with features like rev-matching, which can automatically adjust engine speed to match the selected gear during downshifts, enhancing the driving experience.

3.6 Level 2 (Advancements and Challenges in Autonomous Vehicle Technologies: A Comprehensive Review)

Level 2 autonomous vehicles rely on advanced path planning and localization technologies to navigate their environments effectively. Path planning algorithms generate optimal trajectories considering factors such as road conditions, traffic, and safety constraints, enabling the vehicle to make informed driving decisions. Localization algorithms accurately determine the vehicle's position and orientation using sensor fusion techniques and map-based approaches. Challenges such as complex driving scenarios and sensor limitations are being addressed through ongoing research and development, with advancements in machine learning, sensor technology, and mapping services. Improvements in path planning and localization will enhance the capabilities of Level 2 autonomous vehicles, contributing to safer and more efficient semi-autonomous driving experiences.

3.6.1 Path Planning

is typically defined in a purely geometric space, whereas trajectory planning incorporates temporal properties to account for dynamics. The goal is to find an optimal solution that connects the start and goal points, considering smooth maneuvers, minimum distance, and avoiding known obstacles.(Anete Vagale, Rachid Oucheikh, Robin T. Bye, Ottar L. Osen, Thor I. Fossen)

3.6.2 Localization

Electric vehicles and autonomous driving are prominent areas of research in the automotive sector, with a shared goal of achieving safer and more environmentally friendly transportation. A fundamental requirement for autonomous vehicles is the ability to build an accurate map of the environment and localize themselves within it. This paper proposes a two-step approach using a stereo camera sensor and the ORB-SLAM2 package to address the challenges of mislocalization and accumulated errors in live SLAM systems. In the first step, a map of visual features is created and saved at low driving speeds. In the second step, the pre-built map is reloaded, enabling localization on the existing map. This approach improves continuous localization accuracy, reduces computational load, and enables efficient re-localization. Evaluation results using the KITTI dataset and real-world data demonstrate that the proposed method achieves localization accuracy below 1% in feature-rich environments. The provided extension to the ORB-SLAM2 package and its source code facilitate further research and development in this area. By advancing map-saving capabilities and localization techniques, this work contributes to the advancement of autonomous driving technologies.Nobis, F., Papanikolaou, O., Betz, J., & Lienkamp, M. (2020).Vora, A., Agarwal, S., Pandey, G., & McBride, J. (2020)

3.7 Level 3 (Conditional Driving Automation)

Level 3 of autonomy , and also known as conditional driving automation, refers to a level of vehicle autonomy where the driving system can do different tasks such as sensing the environment to record what happened and controlling , but requires human intervention and oversight. In this section we will explore the crtriea related to level 3 : sensor and controlling.

3.7.1 Control

A control model is a systematic portrayal of a controlled system's behavior and interactions. It includes the system's inputs, outputs, internal states, and the control algorithm that is used to modify the system's behavior. By monitoring the system's response to inputs and making real-time modifications via feedback, the model enables engineers to build and optimize control systems. (Tang, J., Shaoshan, L., Pei, S., Zuckerman, S., Chen, L., Shi, W., & Gaudiot, J. L. (2018); Molina, C. B. S. T., De Almeida, J. R., Vismari, L. F., Gonzalez, R. I. R., Naufal, J. K., & Camargo, J (2017)).

3.7.2 Sensor

In the field of autonomous vehicles, sensor plays a crucial role. It can capture, measure, understand, and perceive the surrounding environment. Autonomous vehicles rely on various types of sensors for perceiving the environment which can make logical decisions based on the collected information similar to humans(Citation: Yeong, D.J.; Velasco-Hernandez, G.; Barry, J.; Walsh, J.(2021)).

3.8 Level 4 (High Automation)

The vehicle is capable of full self-driving in specific conditions or environments (e.g., urban areas or highways). In these predefined scenarios, the vehicle can operate without human intervention. However, it may require human control outside these conditions.

Perception

Perception, in the context of autonomous vehicles, refers to the system's ability to interpret and understand its surroundings. It involves gathering information from various sensors and then processing and interpreting that information to create a representation of the environment.

3.8.1 Computer Vision

Computer vision is a field of computer science that enables machines, including autonomous vehicles, to interpret and make decisions based on visual data from the world. It involves the development of algorithms and systems that allow machines to gain a high-level understanding of images or video.

3.8.2 Human-Machine Interface (HMI)

Human-Machine Interface involves the interaction between humans and machines, where the machine can be controlled or monitored by a human. It encompasses the design and implementation of interfaces that facilitate communication and interaction between the human operator and the autonomous vehicle.

3.9 Level 5

Level 5 autonomous vehicles represent the highest level of automation "Full Automation", where no human intervention is required for driving. These vehicles are capable of performing all driving tasks and navigating various road and traffic conditions without the need for human control or supervision. In this level, the vehicles are equipped with advanced sensor systems, artificial intelligence algorithms, and powerful computing capabilities to perceive the environment, make real-time decisions, and execute complex maneuvers. Level 5 autonomy holds great promise for revolutionizing transportation and mobility by offering enhanced safety, efficiency, and accessibility. However, to ensure the successful deployment and widespread adoption of these fully autonomous vehicles, it is crucial to evaluate their adaptability to diverse driving scenarios and the passenger experience they provide. In this section, we will explore the evaluation criteria related to adaptability and passenger experience in Level 5 autonomous vehicles.

3.9.1 Adaptability

Adaptability is a crucial factor to consider when implementing Level 5 full automation in autonomous vehicles. The papers provide insights into the concept of adaptability, which can be understood as the ability of autonomous vehicles to effectively operate and navigate in diverse environments, including urban infrastructure and real traffic scenarios. The papers emphasize the importance of adaptability for autonomous vehicles to meet different conditions and challenges, In which it underscores the need for transforming urban infrastructure to accommodate autonomous vehicles. This implies that adaptability encompasses not only the vehicles' navigation abilities in urban environments but also the requirement for infrastructure modifications to support their operations, and focuses on the adaptability of autonomous vehicles in responding to cut-in scenarios in real traffic. This suggests that adaptability involves the vehicles' capability to react and adapt to dynamic and unpredictable situations on the road, such as handling situations where other vehicles merge into their lane. Furthermore, it highlights adaptability within the context of a research platform for autonomous vehicles. Where it describes how the ACTor project aims to provide a flexible and modular platform that can be customized for student research projects and transportation purposes on campus. This indicates that adaptability encompasses the flexibility and modularity of the vehicle's hardware and software systems to accommodate various research needs and transportation requirements. (Waqas, A., & Shishore, E.,2021; Zhao, S., Long, Y., & Chen, J.,2021; Paul, N., Pleune, M., Chung, C., Warrick, B., Bleicher, S., & Faulkner, C.,2018)

3.9.2 Passenger Experience

Passenger experience in autonomous vehicles is an important aspect to consider when evaluating the implementation of Level 5 full automation. The four papers provide insights into passengers' real-life experiences, perceptions, and feelings while traveling in autonomous vehicles under different operating conditions. According to the findings, trust, safety, and security emerge as key factors influencing passengers' attitudes towards using autonomous vehicles. Passengers generally value the reliability and safety of the autonomous systems. Positive experiences enhance their feelings of safety, but they have little tolerance for errors or malfunctions by autonomous vehicles. The studies also indicate that passengers' attitudes towards autonomous vehicles are not significantly influenced by external factors such as winter conditions. Whether passengers are traveling in heavy winter conditions or normal operating conditions, their overall perceptions and attitudes towards autonomous vehicles remain consistent. Gender differences do not play a significant role in passengers' perceptions of traffic safety, personal security, and emergency management. However, younger passengers tend to feel better about their personal security on board, while students feel more confident about their ability to act in case of an emergency compared to employed individuals.(Launonen, P., Salonen, A. O., & Liimatainen, H.,2021; Mouratidis, K., & Serrano, V. C.,2021; Salonen, A. O., & Haavisto, N.,2019; Paddeu, D., Parkhurst, G., & Shergold, I.,2020)

3.10 Flow of criteria

The criteria flow across autonomy levels unfolds in a structured progression, commencing with Level 0's foundational components, namely the Emergency Braking System and Airbag. This foundational framework then evolves seamlessly as each subsequent autonomy level introduces and builds upon its unique set of criteria. Level 1 extends the criteria with elements such as Adaptive Cruise Control, Lane Control, Steering, and Gear. Progressing to Level 2, the criteria incorporate Decision Planning, specifically Path Planning and Localization, enriching the autonomous capabilities. Level 3 integrates Control Modules and Perception, inclusive of Ultrasonic, Camera, LiDAR, GPS, and Radar sensors. Level 4 advances the criteria by introducing Perception through Recognition Models, involving Computer Vision and Human-Machine Interface. Finally, Level 5 culminates in the comprehensive framework by adding criteria for Adaptability and Passenger Experience. This systematic evolution highlights the iterative nature of criteria development, with each autonomy level intricately contributing to the holistic framework of autonomous vehicle technology.

3.11 Validation of the framework :

Our framework meticulously examines each level of autonomy, ranging from Level 0 to Level 5, elucidating the specific criteria associated with each level. Moreover, it emphasizes the interconnected nature of these autonomy levels, highlighting how advancements in one level lay the groundwork for the capabilities of the next. It not only outlines the distinctive characteristics of each level but also emphasizes the symbiotic relationship that exists between them, ultimately leading to a fully autonomous driving experience.

In comparison to the older framework, our comprehensive approach stands out for its thorough coverage of all levels of autonomy. Notably, the identified distinction lies in the previous framework's limitation, as it did not encompass the entire spectrum of autonomy levels. Our meticulous design ensures an exhaustive analysis, starting from Level 0 and systematically progressing through each level up to Level 5.

Commencing with Level 0, our framework thoroughly explores the criteria relevant to this foundational stage, where human control dominates. As we traverse through the levels, the criteria seamlessly extend, with each level building upon the foundations laid by the previous one. Level 1 introduces essential automated features, such as Adaptive Cruise Control (ACC) and steering assistance, establishing the groundwork for subsequent advancements.

Level 2 signifies a significant leap, introducing advancements in path planning and localization technologies that set the stage for intricate decision-making processes in Level 3. At this stage, conditional driving automation is introduced, emphasizing the nuanced interaction between automated capabilities and human intervention—a consistent theme in our framework.

Advancing to Level 4, our framework captures the transition to high automation, emphasizing the integration of computer vision, perception, and Human-Machine Interface (HMI) technologies. Each criterion is meticulously documented, highlighting their collective contribution to achieving a higher degree of autonomy.

The culmination of our framework occurs at Level 5, where vehicles achieve full autonomy without any reliance on human intervention. At this pinnacle, our framework elucidates the intricate details of criteria such as adaptability, passenger experience, and infrastructure compatibility—crucial components that synergistically enable fully autonomous driving.

In essence, our framework, when compared to a specific older model, excels in providing a coherent and connected narrative that traces the evolution of autonomous vehicles level by level. By ensuring a thorough examination of criteria at each stage, the framework establishes a clear connection and extension from foundational autonomy at Level 0 to the pinnacle of fully autonomous driving at Level 5. This approach contributes to a nuanced understanding of the technological journey, emphasizing the interdependence and seamless progression that characterizes the development of autonomous vehicle technology.

4 Methodology

4.1 Stage 1: Search Methods

In this initial stage, our goal is to identify relevant literature comprehensively. To achieve this, we will employ a systematic search strategy across various databases, including Google Scholar, Saudi Digital Library (SDL) .The search terms will be carefully chosen to capture the diverse aspects of autonomous vehicles and Boolean operators will be used to refine and expand the search as necessary as tabel 1

Base	**Protocol**
Saudi Digital Library (SDL)	search keywords : • ((autonomous vehicles OR self-driving) AND (emergency braking system OR air bagOR standard cruise control) AND(level0)) • ((autonomous vehicles OR self-driving) AND (accelerating OR adaptive cruise control OR steering OR lane control OR gear) AND(level1)) • ((autonomous vehicles OR self-driving) AND (path planning OR world map OR localisation) AND(level2))
Google Scholar	search keywords : • ((autonomous vehicles OR self-driving) AND (perception OR sensor)) AND (level 3) AND (LiDAR OR camera OR radar OR gps OR ultrasonic)) • ((autonomous vehicles OR self-driving) AND (Perception OR Recognition OR Computer vision OR Image processing) AND(level4)) • ((autonomous vehicles OR self-driving) AND (Fully auto OR adaptability OR passenger experience) AND(level4))

Table 1: Search Protocals

4.2 Stage 2: Paper Collection

Once the search is complete, identified papers will undergo a two-step screening process. In the first step, titles and abstracts will be screened to eliminate irrelevant studies. The second step involves a full-text review to assess the eligibility of the remaining papers based on our predefined inclusion and exclusion criteria in tabel 2

Criteria Type	**Description**
Language	**Exclude** any non-English papers
Title and Abstract	**Include** papers where the title/abstract includes: • autonomous vehicle • level of autonomy • self-driving • autonomous car • Cruise Control
Full-Text	**Exclude** papers where: • The paper doesn't include any of the specified criteria. • The paper isn't relevant to at least two questions. • Papers that are prior to 2017.

Table 2: Paper selection based on criterion.

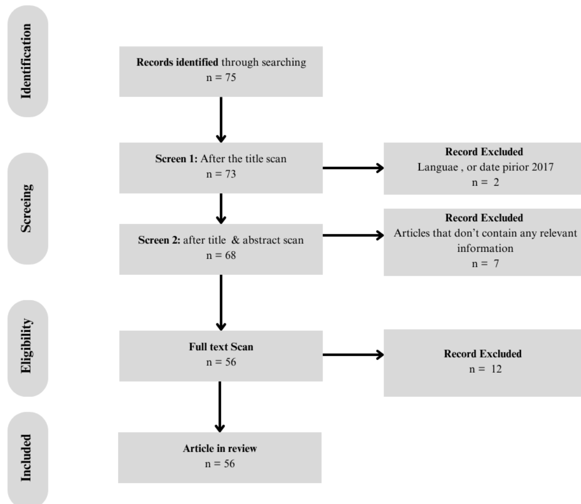

Figure 4: Flow diagram showing process of inclusion and exclusion of papers in the study

4.3 Stage 3: analysis phase

The third phase involved analyzing the chosen selected-paper articles. To assess them, a checklist was developed encompassing all the categories and subcategories within the framework. The elementary criteria that would be used to validate the framework are the level of autonomy. Each level has a sub-criteria related to the method used. The details are described below as follows:

4.3.1 Level 0:

- Emergency Braking System
- Airbag
- Standard Cruise Control

4.3.2 Level 1:

- Accelerating (Adaptive Cruise Control)
- Steering
- Lane Control
- Gear

4.3.3 Level 2:

- Path Planning
- World Map
- Localization

4.3.4 Level 3:

- Control Modules
- Perception (Sensor)
  - LiDAR
  - Camera
  - Radar
  - GPS
  - Ultrasonic

4.3.5 Level 4:

- Perception (Recognition)
  - Computer Vision
- Human-Machine Interface (HMI)

4.3.6 Level 5:

- Adaptability
- Passenger Experience

List of all papers	
1. Kudarauskas	2. Magdici and Althoff
3. Berntorp, Quirynen, and Di Cairano	4. He, Ciuffo, Zhou, *et al.*
5. Yang, Yang, Wu, *et al.*	6. Alsuwian, Saeed, and Amin
7. Franco, Alves Ribeiro, and Sánchez-Arce	8. Chae, Jeong, Lee, *et al.*
9. He, Liu, Lv, *et al.*	10. Hu, Xiong, Zha, *et al.*
11. Claussmann, Revilloud, Gruyer, *et al.*	12. Vagale, Oucheikh, Bye, *et al.*
13. Lv, Cao, Zhao, *et al.*	14. Zheng, Li, Yang, *et al.*
15. Nobis, Papanikolaou, Betz, *et al.*	16. Reid, Neish, *et al.*
17. Vora, Agarwal, Pandey, *et al.*	18. Launonen, Salonen, and Liimatainen
19. Mouratidis and Serrano	20. Salonen and Haavisto
21. Paddeu, Parkhurst, and Shergold	22. Yeong, Velasco-Hernandez, Barry, *et al.*
23. Lin, Sun, Wu, *et al.*	24. Kukkala, Tunnell, Pasricha, *et al.*
25. Xu, Yan, Jia, *et al.*	26. Fayyad, Jaradat, Gruyer, *et al.*
27. Mohamed, Ren, El-Gindy, *et al.*	28. Paul, Pleune, Chung, *et al.*
29. Azfar, Li, Yu, *et al.*	30. Fujiyoshi, Hirakawa, and Yamashita
31. Galvao, Abbod, Kalganova, *et al.*	32. Zou, O'Hern, Ens, *et al.*
33. Schneider, Hois, Rosenstein, *et al.*	34. Tang, Shaoshan, Pei, *et al.*
35. Molina, De Almeida, Vismari, *et al.*	36. Zhao, Long, Chen, *et al.*
37. Zhang, Sheppard, Lipman, *et al.*	38. Drexler, Takács, Nagy, *et al.*
39. Thomas, McCrudden, Wharton, *et al.*	40. Omeiza, Webb, Jirotka, *et al.*
41. Penmetsa, Adanu, Wood, *et al.*	42. Yan, Rampino, Caruso, *et al.*
43. Morgan, Voinescu, Williams, *et al.*	44. Kettwich, Schrank, and Oehl
45. Fu, Mertz, and Dolan	46. Royo and Ballesta-Garcia
47. Lim, Keoh, and Thing	48. Naranjo, Serradilla, and Nashashibi
49. Arifin, Suprapto, Prasetyowati, *et al.*	50. Xu, Dong, Liu, *et al.*
51. Olofsson and Nielsen	52. Darweesh, Takeuchi, Takeda, *et al.*
53. Said, Talj, Francis, *et al.*	54. Porkolab and Lakatos
55. Yang, Zhang, Yu, *et al.*	56. Hubmann, Becker, Althoff, *et al.*

Table 3: Articles selected for review

5 Result

The 56 articles that underwent analysis are listed in table 3. First, the general data about the publications are presented and then the groups and subgroups that make up the frameworks are analyzed. An overview of the publications reveals the following categorization: There were 4 papers addressing level zero, 8 papers focusing on level one, 9 papers centered around level two, 12 papers delving into level three, 11 papers discussing level four, and 9 papers exploring level five.

5.1 Level 0

Level 0 , also known as "No automation," describes the absence of autonomous features or support systems in vehicle autonomy. In this level, humans have full control over the vehicle, without any automatic assistance. The driver is solely responsible for all aspects of driving, including acceleration, braking, steering, and monitoring the surroundings. Cars at Level 0 lack advanced sensors, algorithms, and decision-making abilities found in vehicles with higher levels of autonomy. Consequently, like conventional non-autonomous cars, they depend entirely on the driver's skills and attention.

Criteria	References
The emergency braking system	[5] [6]
Airbag	[7] [54]

Table 4: level 0 criterions

5.1.1 The emergency braking system

primarily relies on traditional braking technologies and does not involve autonomous intervention. These vehicles are equipped with conventional braking systems that function based on the driver's input. When the driver presses the brake pedal, the system activates the mechanical components to reduce speed or bring the vehicle to a complete stop.

5.1.1.1 Non-linear Speed Controller

emergency braking system (EBS) with a non-linear speed controller. The non-linear speed controller is designed to facilitate the autonomous emergency braking system (AEBS) in applying the brakes during an emergency situation. We can infer that the non-linear speed controller is a crucial component of the AEBS, which aids in controlling the vehicle's speed during emergency braking scenarios.

5.1.1.2 Fault Tolerance

Fault tolerance ensures that the system remains operational and can effectively detect and respond to forward collisions even if there is an error or failure in the measurement of any one sensor. This is important because relying on a single sensor for collision detection may introduce vulnerabilities and increase the risk of accidents.

Emergency braking system characteristics	References
Non-linear Speed Controller	[6]
Fault tolerance	[6]

Table 5: Emergency braking system characteristics

5.1.2 Airbag

An airbag is a safety feature in cars that rapidly inflates in the event of a collision, creating a protective barrier between occupants and hard objects. Its purpose is to reduce the impact forces experienced by individuals, thereby minimizing injuries. Airbags work in conjunction with seat belts to provide optimal protection.

5.1.2.1 Crash Detection

Crash detection in airbags refers to the airbag system's capacity to identify and recognize a crash or collision event that necessitates the deployment of the airbags. Sensors like as accelerometers and impact sensors are used to detect rapid changes in vehicle acceleration, deceleration, or external impact forces. When certain specified criteria are surpassed, the accident detection system analyzes sensor data in real time and deploys the airbags. The purpose of crash detection in airbag systems is to guarantee that airbags are deployed in a

5.1.2.2 Occupant Position :

The spatial location, posture, and placement of vehicle occupants within the vehicle cabin is referred to as occupant position. Occupant position detection in the context of occupant safety systems, such as airbags, involves the use of various sensors, such as seat sensors, weight sensors, or depth cameras, to determine the precise position and presence of occupants. The occupant position detection system collects and analyzes sensor data to determine the number of occupants, their seating locations, and any potential impediments to the deployment and effectiveness of safety systems. Accurate occupant position data is required for optimizing the deployment of safety measures such as airbags, seat belt pretensioners, or adaptive safety features to provide customized and effective protection tailored to each occupant's position and characteristics.

Airbag	References
Crash Detection	[54]
Occupant Position	[54]

Table 6: Airbag

5.2 Level 1

Level 1 serves as an introductory stage for vehicle automation, providing partial assistance with driving tasks while emphasizing the driver's crucial role in ensuring safety and efficiency. At this level, the vehicle is equipped with a single automated system for driver assistance, such as steering or acceleration (e.g., cruise control). Adaptive cruise control is an example of this, where the vehicle can maintain a safe distance from the car ahead. Each aspect represents a specific level of autonomy and assistance provided by the vehicle, while still requiring the driver's ongoing involvement and supervision throughout the driving process at Level 1 autonomy.

Criteria	References
Adaptive Cruise control	[1] [2] [48]
steering	[3] [49]
Lane control	[8] [51]
Gear	[50]

Table 7: level 1 criterions

5.2.1 Adaptive Cruise Control

Adaptive Cruise Control (ACC) is an advanced driver assistance system that falls into the Level 1 autonomy category in vehicle automation. It builds upon traditional cruise control by integrating intelligent features that adapt to the dynamic traffic conditions, resulting in a more sophisticated and responsive driving experience. The primary purpose of Adaptive Cruise Control is to automatically adjust the vehicle's speed to maintain a safe distance from the vehicle in front. ACC utilizes sensors, radar, or cameras to continuously monitor the road and the distance to the leading vehicle. Based on this information, the system adjusts the vehicle's speed, decelerating or accelerating as needed to maintain a predetermined and safe gap.

5.2.1.1 Speed Adjustment:

In the realm of vehicle automation, the sub-criterion of speed adjustment represents a pivotal feature aimed at enhancing driving safety and efficiency. Automated systems, such as Adaptive Cruise Control (ACC), play a crucial role in dynamically modifying the vehicle's speed based on real-time traffic conditions and the distance from the vehicle in front. Leveraging a combination of sensors, radar, or cameras, the system continuously monitors the road environment to determine optimal speed adjustments. This sub-criterion reflects the system's adaptability to the ever-changing dynamics of the road, promoting both safety and driver comfort.

5.2.1.2 Maintaining Set Speed:

The ability to maintain a set speed, as specified by the driver, represents another facet of vehicle automation, emphasizing driver preferences and convenience. This feature, commonly associated with traditional cruise control, allows the driver to select a desired speed for the vehicle to consistently maintain, particularly on open roads or highways.

Accelerating criterion	References
Speed Adjustment	[1][2][4][48]
Maintaining Set Speed	[1][2][4]

Table 8: Accelerating criterion

5.2.2 Steering

The steering component plays a crucial role in driver assistance systems. At Level 1, the primary focus of the automated system is to provide partial assistance in steering while emphasizing the ongoing involvement of the driver in ensuring safe and effective control of the vehicle. In Level 1, steering assistance is often implemented through systems that reduce the physical effort required for steering, enhancing driver comfort, particularly in specific driving conditions. Examples of such systems include Electric Power Steering (EPS). These systems strike a crucial balance between automation and driver engagement, ensuring that the driver remains prepared to take control in the event of unexpected situations or challenges on the road.

5.2.2.1 Lane Keeping Assist:

Lane Keeping Assist (LKA) represents a pivotal sub-criterion designed to support the driver in maintaining the vehicle within the designated lane on the road. This feature employs advanced sensors, cameras, or other detection mechanisms to monitor the vehicle's position in relation to lane markings. When the system detects an unintended departure from the lane, without the activation of turn signals, it intervenes with gentle steering corrections to guide the vehicle back into its lane

5.2.2.2 Electric Power Steering (EPS)

EPS is an advanced steering system that utilizes electric motors to assist the driver in turning the steering wheel. Unlike traditional hydraulic power steering systems that rely on a hydraulic pump driven by the engine, EPS systems use an electric motor to provide the necessary steering assistance. This technology has become increasingly popular in modern vehicles due to its efficiency, versatility, and potential for integration with other advanced driver assistance systems.

Steering criterion	References
Lane Keeping Assist	[3][9]
Electric Power Steering (EPS)	[3][9][49]

Table 9: Steering criterion

5.2.3 Lane control

Lane control plays a vital role in Level 1 autonomy in vehicle automation, highlighting the system's capability to assist the driver in keeping the vehicle within the designated lane on the road. At this level, lane control typically involves technologies that offer support and guidance to the driver, enhancing safety and stability during driving.

5.2.3.1 Lane Departure Warning:

This alerts the driver through visual or auditory cues if the vehicle starts to unintentionally leave its lane without signaling. It serves as a safety measure to prevent potential accidents due to unintentional lane departures.

5.2.3.2 Lane Centering:

While not fully maintaining the vehicle in the center of the lane at this level, it assists in reducing the vehicle's tendency to drift away from the intended lane position.

Lane control criterion	References
Lane Departure Warning	[8][10][51]
Lane Centering	[8][10]

Table 10: Lane control criterion

5.2.4 Gear

The gear component primarily pertains to the transmission system and the driver's ability to control the vehicle's gears. In Level 1 autonomy, automated gear shifting is typically not involved. The driver maintains complete control over gear selection and engagement. However, some vehicles may have manual transmissions equipped with features such as rev-matching. These features automatically adjust the engine speed to match the selected gear during downshifts, enhancing the driving experience.

5.2.4.1 Automatic Transmission:

This system eliminates the need for the driver to manually shift gears, automatically choosing the appropriate gear based on speed and other driving conditions.

gear criterion	References
Automatic Transmission	[50]

Table 11: gear criterion

5.3 Level 2

Level 2 autonomous vehicles rely on advanced technologies for path planning and localization to effectively navigate their surroundings. Path planning algorithms are used to generate optimal trajectories, taking into account factors like road conditions, traffic, and safety constraints. These algorithms enable the vehicle to make informed driving decisions. Localization algorithms accurately determine the vehicle's position and orientation by combining sensor data and map-based techniques. Ongoing research and development are addressing challenges such as complex driving scenarios and limitations of sensors through advancements in machine learning, sensor technology, and mapping services. Enhancements in path planning and localization will improve the capabilities of Level 2 autonomous vehicles, leading to safer and more efficient semi-autonomous driving experiences.

Criteria	References
path planning	[11] [12] [13] [14] [51] [52]
Localization	[15] [16] [17]

Table 12: level 2 criterions

5.3.1 Path Planning

Path planning is usually described in a geometric space, focusing on determining the best route between a start and goal point. On the other hand, trajectory planning takes into account temporal properties and considers the dynamics of the vehicle. The objective is to find an optimal solution that connects the start and goal points while considering factors such as smooth maneuvers, minimum distance, and avoiding obstacles that are already known.

5.3.1.1 Global Planner:

The global planner in OpenPlanner is a crucial component that considers traffic costs annotated in the map, allowing the robot to navigate efficiently by taking into account factors such as congestion or preferred routes. Its goal is to generate a high-level path that guides the robot towards its destination while avoiding obstacles and considering traffic costs. This smooth and optimized global path serves as a reference for the robot's local planner and trajectory tracker, enabling them to achieve low-level control and execute the planned trajectory. By taking into account the map, goal position, and traffic costs, the global path planning component in OpenPlanner plays a vital role in enabling the robot's navigation to be both efficient and responsive to traffic-related considerations.

5.3.1.2 Local Path Planner:

Algorithm for autonomous vehicle navigation. Local path planning involves generating an optimal trajectory that allows the vehicle to follow a global reference trajectory while avoiding obstacles in a smooth and comfortable manner within the constraints of road driving. The algorithm calculates a path based on predefined waypoints that describe a global map. These waypoints form a reference frame for generating candidate paths, which start with a transient phase and then follow a curve parallel to the road. Each candidate path, associated with a desired velocity profile, is evaluated using a cost function that considers passenger comfort, obstacle avoidance, and trajectory tracking. The chosen trajectory is applied to a full vehicle model with a coupled longitudinal/lateral controller, validated using the SCANeR studio simulator. The algorithm utilizes the curve interpolation method, generating trajectories with specific geometric shapes and meeting conditions related to vehicle dynamics, comfort, and road shape. Evaluation involves distance and time costs, acceleration, collision verification, and other factors. This local path planning algorithm contributes to autonomous navigation systems by generating smooth and safe trajectories in real-time, considering various criteria and constraints for efficient and comfortable vehicle navigation.

Path planning	References
Global Planner	[11][12][53][52]
Local Path	[11][12]

Table 13: Path planning

5.3.2 Localization

The automotive industry is actively researching electric vehicles and autonomous driving to create safer and more environmentally friendly transportation solutions. A crucial requirement for autonomous vehicles is the ability to accurately map their surroundings and determine their position within that map. This study presents a two-step approach that utilizes a stereo camera sensor and the ORB-SLAM2 package to address challenges related to mis-localization and accumulated errors in real-time SLAM systems. In the first step, a map of visual features is created and saved during low-speed driving. In the second step, the pre-built map is reloaded, facilitating localization on the existing map. This approach enhances continuous localization accuracy, reduces computational load, and enables efficient re-localization. Evaluation results using the KITTI dataset and real-world data demonstrate that the proposed method achieves localization accuracy below 1% in environments with rich visual features. The extension provided to the ORB-SLAM2 package, along with its source code, promotes further research and development in this field. By advancing map-saving capabilities and localization techniques, this work contributes to the progress of autonomous driving technologies.

5.3.2.1 Localization Criteria

after conducting thorough research, we have determined that there are no specific sub criteria identified within the localization aspect discussed.

5.4 Level 3

Level 3 autonomous vehicles, recognized as conditional driving automation, characterize a stage of vehicle autonomy where the driving system is capable of tasks like environmental sensing and control. However, human intervention and oversight remain necessary. This segment delves into the criteria associated with Level 3, encompassing sensors and control mechanisms.

Criteria	References
Control	[34] [35] [55] [56]
Sensor	[22] [23] [24] [25] [26] [34] [45] [46] [47]

Table 14: level 3 criterions

5.4.1 Control

A control model serves as a systematic representation of how a controlled system behaves and interacts. It encompasses the system's inputs, outputs, internal states, and the control algorithm employed to modify the system's behavior. Through monitoring the system's response to inputs and implementing real-time adjustments through feedback, engineers can construct and optimize control systems using this model.

5.4.1.1 Decision Making

The process of choosing appropriate actions or strategies based on the desired objectives and the system's current state is referred to as decision making in the context of control models. Making decisions in control systems entails assessing the information at hand, weighing the pros and cons of various options, and choosing the best course of action to meet predetermined goals or achieve desired system performance. Mathematical models, algorithms, and optimization techniques are frequently used in this process to determine the best control inputs or setpoints to direct the system toward the intended trajectory or state. Control models use decision making to maximize system behavior, improve performance, guarantee stability, and meet predetermined goals or constraints. It is essential to many fields, including industrial automation, robotics, autonomous vehicles, and process control, where intelligent and adaptive decision-making mechanisms are required to achieve desired outcomes.

5.4.1.2 Perception

Perception is the process of gathering, interpreting, and comprehending sensory information from one's surroundings in order to make informed decisions and take appropriate actions. It entails combining various sensors, such as cameras, lidar, radar, and other perception technologies, to collect data about the surrounding environment. The sensory data is then processed and analyzed in order to extract relevant features, detect objects, estimate their positions, velocities, and other relevant attributes. Perception is important in control models because it provides critical input for decision-making algorithms and allows the system to interact with the environment effectively. It enables the control model to perceive and comprehend the current state of the environment, detect obstacles, identify relevant objects, and adapt control actions to achieve desired goals such as navigation, object avoidance, or path planning.

Control	References
Decisions Making	[56]
Perception	[55]

Table 15: Control

5.4.2 Sensor

In the realm of autonomous vehicles, sensors play a pivotal role, capturing, measuring, understanding, and perceiving the surrounding environment. These vehicles depend on diverse sensor types to perceive their surroundings, enabling them to make logical decisions based on the gathered information, akin to human cognitive processes.

5.4.2.1 Ultrasonic Sensors

Ultrasonic sensors are devices that use high-frequency sound waves that are beyond the range of human hearing to detect and measure distances to objects. They emit ultrasonic pulses and calculate the time it takes for the pulses to bounce back after hitting an object, enabling them to determine the distance between the sensor and the object. Ultrasonic sensors are commonly used in applications such as obstacle detection, distance measurement, and parking assistance systems.

5.4.2.2 Camera

The camera is one of the sensor types that is widely used for perceiving the environment. Cameras operate by detecting light emitted from the environment and capturing it on a photosensitive surface through a lens for the production of a clear image of the surroundings.

5.4.2.3 LiDAR

LiDAR is a remote sensing technology that operates by emitting pulses of infrared beams or laser light. These reflections are detected by the instrument, and the interval taken between the emission and receiving of the light pulse enables the estimation of distance. LiDAR scans the environment, and then it generates a 3D representation of the scene.

5.4.2.4 GPS

GPS (Global Positioning System) is a satellite-based navigation system that gives exact position and time data anywhere on the planet. It calculates the distance between the receiver and many satellites using satellite signals, allowing it to estimate its own three-dimensional location (latitude, longitude, and altitude). GPS is widely used for navigation, transportation, mapping, and a variety of other purposes. Its excellent precision and worldwide coverage make it an indispensable instrument in modern life.

5.4.2.5 Radar

Radar (Radio Detection and Ranging) is a technique that detects and locates things in the environment by using electromagnetic radiation. It works by sending out radio waves or microwaves and evaluating the reflections or echoes of those waves when they come into contact with things. Radar systems can estimate the distance, speed, and direction of objects by monitoring the time it takes for the waves to return and studying the variations in frequency (Doppler effect) of the reflected waves. Radar has a wide range of applications, including aviation, maritime navigation, meteorology, military, and automotive systems. It delivers vital information on the presence, location, and movement of objects even in inclement weather and has features like long-range detection and independence from external light.

Sensor	References
Ultrasonic	[47] [24]
Camera	[34] [45] [24] [22]
LiDAR	[46][45][34][26][25][24][23][22]
GPS	[26]
Radar	[22] [24]

Table 16: Sensor

5.5 Level 4

The vehicle has the ability to drive autonomously under specific conditions or environments, such as urban areas or highways. Within these predefined scenarios, the vehicle can function without the need for human intervention. Nonetheless, human control may be necessary outside of these specified conditions.

Criteria	References
Computer Vision	[27] [29] [30] [31]
Perception	[38] [39] [40][41]
Human-Machine Interface (HMI)	[42] [43] [44]

Table 17: level 4 criterions

5.5.1 Computer Vision

Computer vision is a branch of computer science that empowers machines, including autonomous vehicles, to comprehend and make decisions using visual data from the environment. It encompasses the creation of algorithms and systems enabling machines to achieve a comprehensive understanding of images or video content.

5.5.1.1 Sensor Fusion and Integration :

Explore the importance of integrating data and knowledge from different sensors in autonomous systems. Assess the methods and techniques used for sensor fusion, especially in the context of autonomous vehicles

5.5.1.2 Performance Evaluation Metrics:

Investigate the metrics used for evaluating the performance of computer vision models in autonomous systems. Assess the criteria for measuring detection accuracy, speed, and generalization across different hardware.

5.5.1.3 Integration of Deep Learning in Autonomous Systems:

The study explores the application of deep learning techniques, specifically deep neural network architectures, in autonomous systems, focusing on their enhancement in control, perception, motion planning, and image recognition, while also evaluating the implications and challenges of this integration in sensor fusion and computer vision.

Computer vision	References
Sensor Fusion and Integration	[31][30][29][27]
Performance Evaluation Metrics	[31][30][27]
Integration of Deep Learning in Autonomous Systems	[29][27]

Table 18: Computer vision

5.5.2 Perception

In the realm of autonomous vehicles, perception pertains to the system's capacity to interpret and comprehend its surroundings. It encompasses the collection of data from diverse sensors, followed by the processing and interpretation of that data to formulate a representation of the environment.

5.5.2.1 Situation Awareness (SA) :

involves drivers' cognitive understanding of their surroundings during transitions. Integrating SA into control-oriented models is vital for simulating and enhancing handover processes. The ultimate goal is to build a comprehensive simulator for efficient SA assessment in autonomous vehicles[38].

5.5.2.2 Control-Oriented Human Driver Models

enhance driver performance by combining psychological and physiological elements for improved simulations of autonomous vehicle handover processes[38].

5.5.2.3 Future Survey Recommendations :

Utilize a multi-perspective survey approach to understand AV acceptance, conduct real interaction trials, and explore correlations for practical insights and nuanced recommendations for AV development[39].

5.5.2.4 Direct Interaction Experience:

Attitude change refers to alterations in individuals' perceptions of autonomous vehicles (AVs), influenced by direct interaction experiences. Positive attitudes, particularly among vulnerable road users like pedestrians and bicyclists, reflect a favorable transformation in their perceptions of AVs[41].

perception	References
Situation Awareness (SA)	[39][38]
Control-Oriented Human Driver Models	[38]
Future Survey Recommendations	[40][39]
Attitude Change	[41]

Table 19: perception

5.5.3 Human-Machine Interface (HMI)

Human-Machine Interface (HMI) entails the interaction between humans and machines, enabling human control or monitoring of the machine. It involves designing and implementing interfaces that facilitate effective communication and interaction between the human operator and the autonomous vehicle.

5.5.3.1 User Acceptance Models(UAMs):

frameworks that predict and assess users' adoption of technology or systems, considering factors like ease of use, usefulness, behavioral intention, and external variables, based on psychological and sociological theories.

5.5.3.2 Safety and Reliability:

The interface system ensures the reliability and dependability of the vehicle, particularly in situations where automation capabilities may be exceeded, allowing for secure control transfer.

5.5.3.3 Impact of External HMI on Vulnerable Road Users (VRUs):

The study examines the impact of external HMI on vulnerable road users (VRUs), focusing on how visual and communicative elements on autonomous vehicles affect their perception, understanding, and acceptance by pedestrians and cyclists in shared spaces.

Human-Machine Interface (HMI)	References
User Acceptance Models(UAMs)	[42]
Safety and Reliability	[44][43]
Impact of External HMI on Vulnerable Road Users (VRUs)	[44][43][42]

Table 20: Human-Machine Interface (HMI)

5.6 Level 5

Level 5 autonomous vehicles represent the highest level of automation "Full Automation", where no human intervention is required for driving. These vehicles are capable of performing all driving tasks and navigating various road and traffic conditions without the need for human control or supervision. In this level, the vehicles are equipped with advanced sensor systems, artificial intelligence algorithms, and powerful computing capabilities to perceive the environment, make real-time decisions, and execute complex maneuvers. Level 5 autonomy holds great promise for revolutionizing transportation and mobility by offering enhanced safety, efficiency, and accessibility. However, to ensure the successful deployment and widespread adoption of these fully autonomous vehicles, it is crucial to evaluate their adaptability to diverse driving scenarios and the passenger experience they provide. In this section, we will explore the evaluation criteria related to adaptability and passenger experience in Level 5 autonomous vehicles.

Adaptability	[28] [36] [37]
Passenger Experience	[18] [19] [20] [21] [32] [33]

Table 21: level 5 criterions

5.6.1 Adaptability

Adaptability is critical for implementing Level 5 full automation in autonomous vehicles, emphasizing their ability to navigate diverse environments and real traffic scenarios. The papers underscore the need for infrastructure adjustments to support operations, focusing on adaptability in handling real traffic challenges like cut-in scenarios. The concept extends beyond navigation, requiring flexibility in infrastructure and the ability to react dynamically to unpredictable road situations. The ACTor project illustrates this adaptability, offering a modular platform for student research and campus transportation, showcasing the flexibility of hardware and software systems to meet various needs.

5.6.1.1 Infrastructure Compatibility

Autonomous vehicles need to be compatible with existing urban infrastructure, such as roads, traffic control systems, and parking facilities. This means they should be able to navigate and operate safely within the current infrastructure without the need for significant modifications. Adaptability to the existing infrastructure is crucial for the seamless integration of autonomous vehicles into urban environments

5.6.1.2 Sensor Integration

Autonomous vehicles rely on various sensors, including cameras, lidar, radar, and GPS systems, to perceive their surroundings and make informed decisions. It is essential for these vehicles to be adaptable to different sensor technologies and capable of integrating multiple sensors effectively. By processing sensor data, autonomous vehicles can accurately understand the environment, detect obstacles, and navigate safely

5.6.1.3 Software Modularity

The software systems of autonomous vehicles should follow modular design principles, such as those provided by the Robot Operating System (ROS). This modularity enables easy development, modification, and integration of new features and functionalities. By adopting a modular approach, autonomous vehicles can quickly adapt to different research projects or hardware changes, allowing for efficient software development and enhancement

5.6.1.4 Real-Time Decision-Making

Autonomous vehicles need to possess adaptable software systems that are capable of making real-time decisions. They should be able to analyze sensor data in real-time, interpret complex traffic situations, and react promptly to changing conditions. This adaptability is crucial, especially in scenarios like cut-in situations or encountering unexpected obstacles, where the vehicle's decision-making capabilities play a vital role in ensuring safety and efficient navigation

5.6.1.5 Scalability & Global Applicability

Autonomous vehicle platforms should be adaptable to accommodate future advancements in technology and research. They should provide a scalable framework that can incorporate new hardware components, algorithms, and software updates as they become available, ensuring long-term adaptability and compatibility. Autonomous vehicles should demonstrate adaptability across different geographical regions and international contexts. This includes considering factors such as traffic regulations, road conditions, cultural norms, and user preferences, to ensure the global adaptability and acceptance of autonomous driving technology

Adaptability	References
Infrastructure Compatibility	[37]
Sensor Integration	[36]
Software Modularity	[28]
Real-Time Decision-Making	[28][37]
Scalability AND Global Applicability	[45]

Table 22: Adaptability

5.6.2 Passenger Experience

Examining the implementation of Level 5 full automation in autonomous vehicles includes a crucial evaluation of passenger experience. The four papers offer valuable insights into passengers' real-life experiences, feelings, and perceptions across different operating conditions. Trust, safety, and security emerge as pivotal factors influencing passengers' attitudes, with a strong emphasis on valuing the reliability and safety of autonomous systems. Positive experiences contribute to a sense of safety, while any errors or malfunctions diminish passenger tolerance. External factors like winter conditions do not significantly impact attitudes, maintaining consistency across diverse scenarios. Gender differences have minimal influence on perceptions of traffic safety, personal security, and emergency management, but younger passengers express greater confidence in personal security, and students feel more capable in emergency situations compared to employed individuals.

5.6.2.1 Trust, Safety and Security

Trust plays a pivotal role in influencing passengers' attitudes towards autonomous vehicles. Trust in the technology, safety measures, and reliability of autonomous vehicles plays a significant role in determining passengers' comfort and willingness to use them. The research articles emphasize that passengers' perceptions of safety and security are crucial factors in shaping their attitudes towards autonomous vehicles. Passengers need to feel safe and secure while traveling in autonomous vehicles, and any concerns regarding safety risks need to be addressed effectively

5.6.2.2 Operating Conditions

The studies consider the impact of different operating conditions on passengers' experiences. This includes exploring passengers' attitudes towards autonomous vehicles in various weather conditions, such as heavy winter conditions or icy roads. Understanding how operating conditions affect passengers' perceptions is essential for designing effective autonomous transportation systems

5.6.2.3 Quantitative and Qualitative Data

Both articles utilize a combination of quantitative and qualitative data collection methods. Quantitative data, such as surveys, are used to gather information on passengers' beliefs, attitudes, and evaluations of outcomes. Qualitative data, such as interviews, provide deeper insights into passengers' real-life experiences, perceptions, and feelings related to autonomous vehicles

Passenger Experience	References
Trust, Safety and Security	[21] [20] [18]
Operating Conditions	[21] [20]
Quantitative and Qualitative Data	[18] [19] [20] [21]

Table 23: Passenger Experience

Conclusion

This systematic review presents a comprehensive analysis of the literature on vehicle autonomy frameworks from 2017 to 2023. The study examines various levels of autonomy and their associated features, providing valuable insights into the evolution of autonomous vehicles. The review highlights the progression of autonomy levels, starting from Level 0, which represents manual control, to Level 1, characterized by driver assistance features. At Level 2, semi-autonomous capabilities such as adaptive cruise control, lane-keeping assist, and electric power steering are introduced, enhancing the driving experience. Moving further, Level 3 introduces conditional driving automation, where control models and sensors play a crucial role in decision-making. Level 4 focuses on high automation, incorporating advanced technologies like sensor fusion with ultrasonic sensors, cameras, LiDAR, GPS, and radar. These technologies enable the vehicle to perceive its surroundings and make informed decisions. Ultimately, Level 5 represents full automation, where the vehicle operates without human intervention. To achieve this level, infrastructure compatibility, sensor integration, software modularity, and real-time decision-making are critical factors. Additionally, global applicability ensures that autonomous vehicles can function effectively across different regions and driving environments. The review also emphasizes the importance of trust, safety, and security in the successful adoption of autonomous vehicles. Factors such as operating conditions and user experiences need to be considered to shape passenger attitudes towards autonomous driving. Furthermore, the integration of advanced technologies and a focus on safety and user experience are key elements for the development and widespread acceptance of autonomous vehicles. In conclusion, this systematic review provides a comprehensive overview of vehicle autonomy frameworks, highlighting the progression from manual control to full automation. The analysis underscores the importance of advanced technologies, safety considerations, and user experiences in shaping the future of autonomous vehicles.

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