FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 11, June, 2026, pp 227 – 241
DOI: https://doi.org/10.33003/fjs-2026-1011-5142

Driving into the Future: A Comprehensive Survey of Autonomous Vehicle Technologies

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ABSTRACT

Autonomous vehicles (AVs) represent a cornerstone of future smart city transportation systems, offering the potential to eliminate human driving errors, reduce traffic fatalities by at least 40% etc. While AV technology is advancing rapidly toward highly automated driving (HAV), commercial realization remains hindered by significant technological uncertainties, soaring development costs, and strict safety-critical validation requirements. This paper provides a holistic survey of autonomous vehicle technology, bridging the gap in existing literature by tracing its historical evolution from 1920s "phantom autos" to modern platforms equipped with LiDAR, cameras, and Vehicle-to-Everything (V2X) communication. Beyond that, it evaluates the modern state of research by benchmarking the three dominant autonomous vehicle software architectures modular pipelines, pure End-to-End (E2E), and hybrid systems across seven quantitative dimensions: planning quality, safety certification, latency, data efficiency, debuggability, Operational Design Domain (ODD) adaptation, and robustness. Comparative analysis of industry-standard benchmarks, reveals that while E2E and hybrid approaches achieve superior planning scores (88–91%) and lower collision rates (1.1–2.0%) than modular pipelines (84–86% planning; 3.95% collisions), pure E2E models lack a viable regulatory path for 2026 L4 deployment due to prohibitive validation mandates exceeding (10^{-11}) simulation miles. Conversely, hybrid modular-E2E algorithms recover approximately 98% of E2E planning performance, drastically reduce debugging times to 2–6 hours, and retain compliance with ISO 26262:2018 ASIL-D safety standards. Ultimately, this work maps out the market landscape and identifies hybrid architectures as the current Pareto-optimal solution balancing operational capability, safety assurance, and immediate regulatory feasibility for L3/L4 automation.

Received: 22 Jan. 2026
Accepted: 12 Feb. 2026
Published: 16 July 2026

Keywords: Autonomous Vehicles, Smart Transportation, Safety, Benchmarks, Autonomous Vehicle Technology, Optimal Algorithms, Architectures, Performance

INTRODUCTION

In recent years, academia and industry have invested enormous human and material resources in the research and development of AVs. One of their original intentions is to reduce the rate of traffic accidents. Every year, the economic loss caused by traffic accidents is 277 billion dollars, which is twice as much as traffic congestion (Parsa et al, 2020). Drivers' errors cause 90% of traffic accidents. More than 40% of fatal crashes are related to alcohol, distraction, drug addiction, and fatigued driving (Stilgoe et al,2021). Even when nonhuman factors primarily cause crashes, they usually include some human factors such as distractions or unfamiliar driving skills. With improved AV technology, fatal accident rates are likely to fall by at least 40%, and human factors may disappear. With, the development of technology, autonomous driving rises and is available to be achieved. There are a lot of exploration on autonomous driving. Autonomous vehicles (AVs) as a part of the intelligent system gets high expectation for improving vehicle operation safety, traffic efficiency, and passengers' experience. AVs offer a wide range of advantages in safety, traffic capacity, vehicular emission, and energy consumption (Emekumeh et al, 2026).

The autonomous vehicles are essential in increasing the communication, control, and level of autonomy of a broad range of applications in land, sea, and air. The increase in workforce age and cost has driven the technological development and adaptation of innovative system design, simulation, and application of intelligence in transport systems. The changing technological demand and operating uncertainties have resulted in new types of transportation challenges and increased demand for sensors and sensor platforms for capturing mobility analytics under uncertain operating environment (Cheng et al,2018). For example, various autonomous vehicles such as unmanned aerial and submersible vehicle for traffic survey, marine sediment transport, and vehicle accident survey are used. For land transport system, the autonomous vehicles such as Google autonomous vehicle and Tesla are focusing on the vehicle's self-information and are developed based on the Light Detection and Ranging (LiDAR) systems, radar, and cameras. The Vehicular-to-Everything(V2X) communication technology enables vehicles to communicate with each other and with surrounding infrastructure access points like roadside units (RSUs) (Xionghu et al, 2018). It can provide global information of the networked vehicles and has drawn extensive attention due to its broad application prospects including advanced driver assistance systems, enhanced collision avoidance, and automatic toll fee collection (Mohammad et el,2018).

At present, the major developed countries regard autonomous driving as an important strategic direction for future development, and this field is also widely concerned by academia and industry. Although unmanned driving is the "ultimate goal" of technology development, "highly automated driving" vehicles (HAVs), which can achieve automated driving function under some specific conditions, may come in the next few years (Merlhiot et al,2021). Autonomous driving is beneficial to society, drivers, and pedestrians. It is not affected by human factors so that the incidence of traffic accidents can almost drop to zero (Bertolazzi et al.,2021). Even with the interference of the rate of traffic accidents of some autonomous driving, the rapid growth of the market share will reduce the overall traffic accident rate (Gonzalez et al, 2021). At the same time, the autonomous driving mode is more energy efficient, green, and environmentally friendly, which is in line with the current international sustainable development needs. Autonomous vehicles are widely expected to: •Increase accessibility for people who are unable to drive themselves; • Reduce the cost of using taxis and delivery services; • Reduce the demand for off-street parking; • Increase road safety and capacity; • Increase the demand for short-stay, on-street parking. Autonomous vehicles have various technologies like radars, sensors, global positioning system (GPS) and on-board cameras that help it to detect the surroundings and navigate. The parts of an autonomous vehicle are highlighted in Figure 1. The data which is sensed using these technologies are fed into advanced control systems present in these vehicles. These systems make relevant decisions regarding navigation and interpreting obstacles that may be present. Also interpreted are traffic signals and signage that help the vehicle to have a smooth movement from a source to a destination while accounting for the nearby vehicles on the road. Even though there are various benefits of using autonomous vehicles, there are also issues related to these vehicles. The costs of these vehicles will generally be higher than the comparable non autonomous vehicles. This is due to the high amount of technology present in these vehicles. The technology itself is not mature enough and still at its early stages, where developments are happening by the day. Other issues include accountability of accidents, security issues of technologies used, privacy issues related to consumer data, insurance regulation issues (Sanctus et al., 2026).

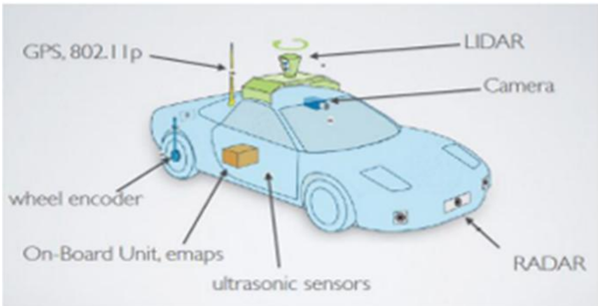

Figure 1: Autonomous Vehicle Components (Firoz et al, 2021)

Till today, the numerous works that had been done have been to explore multiple issues of autonomous vehicle system (Campbell et al, 2010; Okuda et al, 2014). But the majority of surveys focus only on certain aspects of the autonomous vehicle and none of these surveys present a comprehensive (holistic), historical excursus of autonomous vehicles, its elements, its various architectures and method towards autonomous vehicle technology.

A Brief Historical Excursus of Autonomous Vehicles

Autonomous vehicles are becoming more pragmatic from year to year as multi-national companies are racing ahead to build them. The projected value for autonomous vehicles in the global market is at $615 Billion by 2026. According to the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA) autonomous vehicles are "those in which operation of the vehicle occurs without direct driver input to control the steering, acceleration, and braking and are designed so that the driver is not expected to constantly monitor the road way while operating in self-driving mode.". The advancement and rise of autonomous vehicles are due to the significant research results obtained in the arenas of wireless and embedded systems, sensors, communication technologies, navigation, data acquisition, and analysis. They combine sensor and map data and based on machine learning (i.e., "experience"), can classify objects in their surroundings and predict how they are likely to behave, in relation to other moving vehicles, pedestrians and cyclists, stationary objects (e.g., signs, trees, traffic cones) and based on what an AV can "see" and what it predicts nearby objects are likely to do, it can make decisions about speed and steering inputs

The journey of autonomous vehicle began in the year 1920 with the "phan tom autos" concept, which means a remote-control device, which was used to control the vehicle (Lafrance et al,2016). Later in the 1980s self-managed autonomous vehicles were developed. Further, NavLab of Vehiclenegie Mellon University contributed majorly in this field by developing an Autonomous Land Vehicle (ALV) (Kanade et al, 1986). In a major breakthrough in 1987, the "Prometheus project" of Mercedes (Schmidhuber et al,1987), gave the design of their first automated vehicle with the capability of tracking lanes. At that time, it was not completely autonomous, but it had the ability to automatically switch lanes. In the twenty-first century, there is a huge demand for low-cost, high-performance autonomous vehicles. There is a fine line of difference between the two terminologies: the automated vehicle and the autonomous vehicle. The term automated vehicle refers to a vehicle with little human intervention, whereas the term autonomous vehicle refers to a vehicle without any human intervention. The autonomous vehicle is a fully computer-controlled vehicle which can instruct (guide) itself, make its own decisions, familiar with its surrounding without any human interference (intervention).

Elements of Autonomous Vehicles (AV)

Autonomous vehicle (AV) will reduce human errors and is expected to lead to significant benefits in safety, mobility, and sustainability (Shladover et al,2019; Khoury et al, 2022). The autonomous vehicles system involves three main elements: orientation, visibility, and decision, as shown in Figure 2. For each element, certain functions are performed with the aid of one or a combination of technologies. For AV orientation, the position of the vehicle is determined mainly using Global Navigation Satellite System (GNSS). To increase reliability and accuracy, this technology is supplemented with other data gathered from specific perception technologies, such as cameras and internal measurement devices (tachometers, altimeters, and gyroscopes).

The visibility of AV, sometimes referred to as perception, involves infrastructure detection (e.g. sight obstacles, road markings, and traffic control devices) and traffic detection (other vehicles, pedestrians, and cyclists). High-precision (HP) maps help the AV not only perceive the environment in its vicinity, but also plan for the turns and intersection far beyond the sensors' horizons. The other main technology that represents the 'eye' of the AV is the Light Detection and Ranging (Lidar). Other technologies used for infrastructure visibility include video cameras which can detect traffic signals, read road signs, keep track of other vehicles, and record the presence of pedestrians and other obstacles. Radar sensors can determine the positions of other nearby vehicles, while ultrasonic sensors (normally mounted on wheels) can measure the position of close objects (e.g. curbs). Lidar sensors can also be used to identify road features, like lane markings. Three primary sensors (camera, radar, and Lidar) work together to provide AV with visuals of its 3D environment and help detect the speed and distance of nearby objects. The visibility information is essential for the safe operation of the AV. For example, the information can be used to ensure that adequate sight distance (SD) is available and if not to take appropriate actions. The decision of AV is based on the data generated by the AV sensors and HP maps. Examples of the decisions that are made by AV include routing, changing lanes, overtaking vehicles, stopping at traffic lights, and turning at an intersection. The decision is made by an on-board centralized artificial intelligence (AI) computer that is linked with cloud data and include the needed algorithms and software. For the AV to function effectively, it must communicate with the environment as part of a continuously updating, dynamic urban map (NCHRP et al, 2017). This involves vehicle to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. Internet of Things (IoT) technology provides telematics data about the condition and performance of AV, such as real-time location and speed, idling duration, fuel consumption, and the condition of its drive paths.

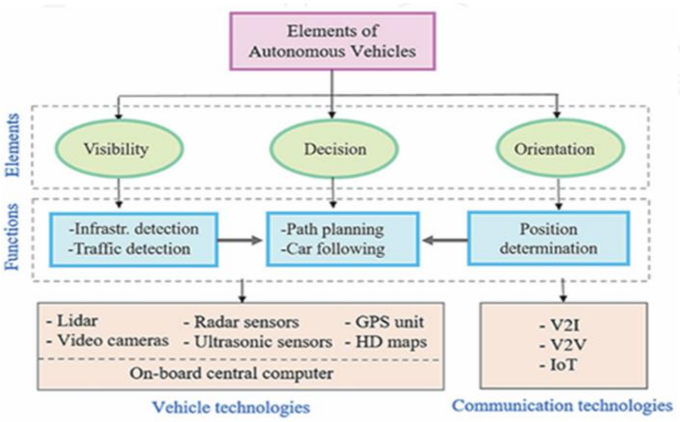

Figure 2: Elements of Autonomous Vehicles and Their Functions and Technologies (Sanctus et al,2026)

Technological Perspective of Autonomous Vehicles (Avs)

Autonomous Vehicles (Avs) operate in various modes, each with distinct characteristics and requirements. The SAE has defined six levels of autonomy, ranging from Level 0 (no automation) to Level 5 (fully autonomous). The table 1 presents each level along with a brief description of the level of automation provided by the vehicle, and examples of features that are commonly found at that level. The table is a useful tool for understanding the different levels of autonomy and the capabilities of autonomous vehicles at each level. It can be used as a reference for comparing different autonomous vehicles based on their level of autonomy and understanding the current state of the technology.

Table 1: Classification of Autonomous Vehicles Based on the Levels of Autonomy as per the Standard Set by the Society of Automotive Engineers (SAE)

S/N	Authors and Years	Level	Name	Technologies	Sensors
1		0	Driver Only		
2	NCHRP et al. (2017)	1	Assisted	Active Cruise Control (ACC) Lane Departure Warning System (LDWS)	Ultrasonic Sensor Long Range Radar (LRR) Camera
3	Mansour et al,(2020)	2	Partial Automation	Lane Keep Assist (LKA) Park Assist (PA)	All Sensors from Level – 1 Short Range Radar (SRR)
4	Gupta et al, (2023)	3	Conditional Automation	Automatic Emergency Braking (AEB) Driver Monitoring (DM) Traffic Jam Assist (TJA) Dead Reckoning (DR)	All Sensors from Level – 2 . LIDAR Long Distance Camera Stereo Camera Thermal Camera

S/N	Authors and Years	Level	Name	Technologies	Sensors
5	NCHRP et al. (2021)	4	High Automation	Sensor Fusion	All Sensors from Level—3
6	Aazam et al. (2021)	5	Full Automation	Automatic Pilot (AP)	All Sensors from Level—3

The vehicle automation classification defined by the Society of Automotive Engineers (SAE, 2021) has been adopted worldwide. Six automation levels (from 0 to 5) are distinguished depending on the on-board driver assistance systems, i.e. on the distribution of the driving tasks between the vehicle and the driver. Vehicles of levels 0 to 2 are called "traditional", because the environment is still monitored by the driver. From level 3 onwards, this task is performed by the vehicle. This is a key frontier, as it involves that the vehicle must collect all the necessary data from the environment and interpret it. Furthermore, the vehicle can take responsibility for the driving task to certain limits. The culmination of automation is reached at level 5, where vehicles are called to perform the whole driving task autonomously, on all types of roads, in all speed ranges and with any weather conditions. Apart, from prototypes, only AUDI offers at present a SAE3-level model to the public. Other automakers currently work on SAE3-and SAE4-level vehicles, which are likely to be available in the short-term.

Agents in Autonomous Vehicle

The main agents in autonomous driving are the vehicles, the infrastructure, the cloud and the passengers' personal devices, which must perform accurately and co-ordinately, supported by reliable communication systems. The vehicle´s provisional architecture varies among companies and research centres. However, four distinct parts can be found in any design: the sensing system, the client system, the action system and the human-machine interface (HMI) (Intel, 2021; Arriola, 2021; Shaheen, 2021).

i. The sensing system is responsible for the data collection from the environment and from other vehicles. Data must be collected in real time and for all types of boundary conditions. Sensing refinement has been achieved by using a diversity of sensors in the vehicle, all of them with different strengths and weaknesses and thus appropriate to support particular aspects of driving assistance. For example, equipping vehicles with a LIDAR sensor led to significant progress, as it provides360º of visibility and measures distances with a precision of ±2 cm. Up to distances of 60 m LIDARs are able to accurately generate 3D maps of the nearby objects, and with less precision for distances up to 500 m. Therefore, LIDARs allow mapping and navigating, but also detecting and tracking obstacles, other cars, pedestrians, etc. A global navigation satellite system is the complement to self-localize the vehicle.
ii. The client system consists of the hardware and operating system needed to process the data. This, computing framework plays a key role, as it must in real time i) extract relevant and accurate information from the raw data supplied by the sensors (perception task) and ii) tell the vehicle how it must proceed (decision task). Very different types of hardware platforms are being designed: some companies opt for computing boxes containing distinct processors and accelerators. Others are developing system-on-chip (SoC) solutions, which are tiny integrated circuits with a microprocessor and advanced peripherals, the latter consuming less energy and having less space requirements, but still without enough computing capabilities to allow both fast and continuous sequential and parallel data processing. The support of cloud computing will be essential in this regard and will also add robustness to the system, which must continue working even after a failure. The perception task includes three parts: localization, detection and tracking, all of them achieved through data fusion performed at different levels. Localization is usually performed by algorithms that fuse data from GPS, IMU and LIDAR, resulting in a high-resolution ground map. Vision-based deep-learning technologies are achieving accurate results for object detection, as they are able to autonomously handle huge amounts of data. Deep Learning techniques have also demonstrated their suitability for object tracking relative to approaches based on computer vision. Decision-taking is one of the most challenging tasks that AVs must perform, especially in awkward situations. It encompasses prediction, path planning and obstacle avoidance, all of them performed on the basis of previous perceptions.
iii. The action system consists of the mechanical parts of the vehicle (steering system, braking system, etc.) which will be probably improved with respect to traditional cars, in line with the other parts of the AV architecture. And finally, the HMI which is called to be minimalist in SAE5-level vehicles, basically oriented to provide information about the driving. (Francesc et al, 2021)

MATERIALS AND METHODS

The study adopts the cyclic action research methodology to conduct this study. Cyclic action research process enables the generation of prescriptive design knowledge through structuring and evaluating collective Information Technology artifacts in an organizational setting as stated by Edje et al (2021). It is mainly comprised of five stages arranged in cyclical pattern. These stages include assessing the current situation, identify issues from the existing situation, devise a plan to resolve the issues, analyze solution and reflect. Therefore, the stages are utilized to actualize the research objectives of this study. Firstly, an investigation was carried out on related existing research works to ascertain the level of utilization of autonomous vehicles in Nigeria and West Africa in supporting intelligent transportation systems in Nigeria in the introductory section of this research. Findings show that there is no significant deployment of autonomous vehicles in supporting intelligent transportation systems in Nigeria (Emekumeh et al,2026). Thereafter, a brief historical excursus of autonomous vehicles, the elements and components of autonomous vehicles are identified in previous researches (see literature review) that may foster the effectiveness and efficient use of autonomous vehicles in supporting intelligent transportation systems in Nigeria, the operational modes of autonomous vehicles, the technological perspective of autonomous vehicles (AVs), its agents and architecture frameworks are explored. After which a plan is devised on how to resolve the issues identified by proposing and formulating various architectures, their functions and usage for autonomous vehicles in supporting intelligent transportation systems. Furthermore, we reflect on the proposed architectures functionality and as well discussions on the optimal algorithms for the proposed architectures for autonomous vehicles.

Figure 3: Cyclic Action Research Methodology (Sanctus et al, 2026)

Architecture Frameworks for Autonomous Vehicles
Architectures are the art, science, and technique of designing and constructing structures in order to blend functional utility with aesthetic appeal. It encompasses the entire process from conceptual sketching to structural planning, defining the form, organization, and relationships of components in both physical buildings and technical systems. Here are some of the architectures for the autonomous vehicles the articles will focus on.

Autonomous vehicle architectures generally consist of four main pillars: perception, localization, planning, and control, working together to enable self-driving capabilities. These systems rely on sensors (LiDAR, camera, radar), AI for decision-making, and V2X communication (vehicle-to-everything) to safely navigate surroundings, with architectures often designed using modular "4 pillars" or "end-to-end" machine learning approaches.

i. The Basic Architecture of an Autonomous Vehicle: This shows the system architecture of the autonomous vehicle, where it shows the areas covered by different components in the vehicle design. Different ranges of situational awareness vary from application to application and it is achieved through multiple components. For instance, prevention of front and rear bumper collisions is done through infrared devices, whereas short-range radars are used for object detection, lane-change cautioning, and traffic view. Equipping autonomous vehicles with a series of cameras for the surrounding views and LIDAR helps in collision avoidance and emergency brakes. Long-range radars help in cooperative cruise control and long-range traffic view construction. Altogether the aforementioned components are networked and work firmly with each other, as shown in Figure 4.

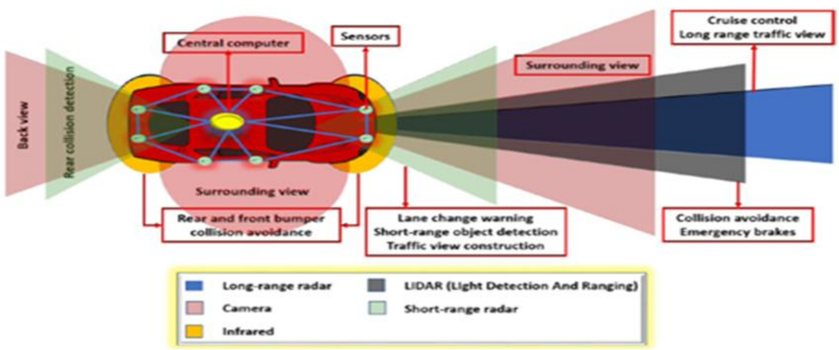

Figure 4: The Basic Architecture Framework of an Autonomous Vehicle

For movement of an autonomous vehicle from one-point A to B, the vehicle performs a number of important steps in an iterative manner until it reaches its destination such as Perceive and aware about its surrounding environment, Path planning and navigation and Controlled movements on the road (Schnabel et al.,2023). After perceiving its surrounding environment, it makes path planning along with its destination information and then starts navigating to reach the destination. A number of controlled movements are exercised for a smooth, safe ride on the road with the help of actuators and sensors (Wang et al.,2021). Electronic Control Units (ECUs) control most of the components electronically. ECUs communicate with each other and with the decision support system through the controller area network (CAN) bus inside each vehicle. During a drive, the autonomous vehicle exhibits a number of manoeuvres which needs both software/hardware support, extensive coordination, and data sharing among different components of the vehicle. The figure 4 displays the basic architecture of an autonomous vehicle. The architecture consists of various components that work together to enable the vehicle to drive itself. The main components of the architecture are Sensors, Perception and Localization, Planning and Control, Communication and Cloud (Sanctus et al,2026).

ii. The functional architecture of an autonomous vehicle is a layered structure which contains data acquisition, data processing and actuation. Data acquisition is performed by the hardware components, such as sensors, radars, cameras, LIDAR, and transceivers (Padmaja et al., 2023).

The collected data is processed by a central computer system, which is later implemented by the decision-support system (DSS). The DSS activates the autonomous vehicle and the situational awareness is actualized through both short- and long-range imaging devices (Moorthy et al., 2023).

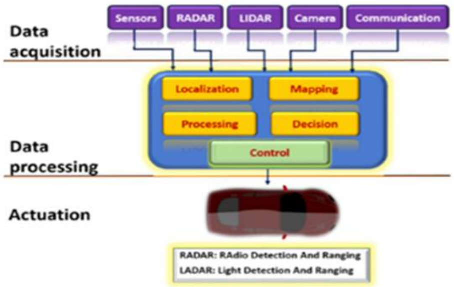

Figure 5: Functional Architecture Framework of an Autonomous Vehicle

The figure 5 displays the functional architecture of an autonomous vehicle. The architecture is divided into several functional blocks, each of which is responsible for a specific set of tasks. The main functional blocks of the architecture are Data Acquisition, Data Processing and Actuation – The components that vehiclery out the commands from the control system like acceleration, braking and steering

As a basic task, gearing of every autonomous vehicle. is performed with numerous actuators and sensors that produce vast amounts of data which must be handled and analyzed to take decisions on time. The amount of data that the vehicle. must handle depends on the levels of autonomy according to Zanchin et al., (2021). The essentials here is the requirement of various sensors and actuators to function autonomously, so that the vehicle. should foresee, decide and maneuver cautiously according to some strategy. A number of fundamental characteristics of autonomous vehicle design are outlined in this section. Figure 4 depicts a number of elevated functional components of a typical autonomous vehicle.

iii. Data flow Architecture of Autonomous is a multi-layered system designed to transform massive volumes of raw sensor data into safe driving actions in real-time. This "sense-plan-act" pipeline involves high-speed data acquisition, complex processing, and low-latency communication.

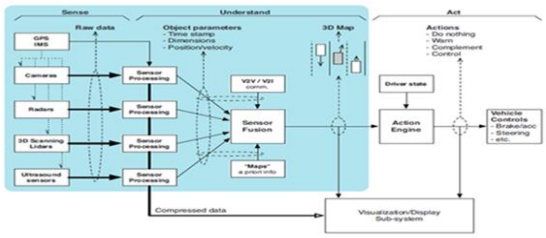

Figure 6: Data Flow Architecture Framework of an Autonomous Vehicle (Firoz et al.,2021)

Data begins at the Sensor Subsystem, where various hardware components capture environmental information through theses stages and processes:

i. Data Acquisition and Perception

Sensors

These include LiDAR for 3D point clouds, RADAR for velocity and distance, cameras for visual recognition, and GPS/IMU for positioning.

Sensor Fusion

Raw data from these complementary sources is merged to create a more accurate and reliable "world model" than any single sensor could provide.

Perception Layer

Software algorithms process this fused data to identify objects (pedestrians, vehicles, signs) and classify them.

ii. Localization and Planning

The processed world model is then passed to the decision-making layers:

Localization

Combines sensor data with high-definition (HD) maps to determine the vehicle's precise position within its environment.

Planning Subsystem

This layer acts as the vehicle's "brain." It performs Route Planning (high-level navigation), Behavior Planning (deciding maneuvers like lane changes), and Trajectory Generation (plotting the exact path).

iii. Control and Actuation

The final stage of the on-vehicle flow translates plans into physical movements:

Control Subsystem

Receives the target trajectory and generates specific commands for steering, braking, and acceleration.

Actuators

These mechanical components execute the electronic commands, closing the loop from sensing to physical action.

iv. Connectivity and Off-Vehicle Flow (V2X)

Modern AVs also integrate external data streams through V2X (Vehicle-to-Everything) communication:

V2V and V2I

Vehicles share safety-critical data with other cars (V2V) and infrastructure like smart traffic lights (V2I).

Cloud/Edge DataOps

Large-scale data is often offloaded to the cloud for long-term storage, model training (MLOps), and fleet-wide analytics to improve performance over time.

v. Architectural Paradigms

Architectures are shifting from traditional central processing to more optimized models:

Distributed (Edge) Processing

Pre-processing data directly at the sensor level reduces the bandwidth required to send information to the central computer.

Dataflow Accelerator Architecture (DAA)

Emerging models that map autonomous workloads directly to hardware templates, improving timing safety and energy efficiency (Emekumeh et al,2026).

Peripherals and reference architecture for an Autonomous Vehicle

Peripheral architecture refers to the specific, concrete physical hardware and electronic components that interface with the real world so as to enable the vehicle to sense its environment and execute actions. These components act as "peripherals" to the central processing unit(s) or "controllers". Some of these are:

i. Physical Components: This includes all the actual sensors, actuators, and communication modules installed on the vehicle, such as LiDAR units, radar, cameras, GPS receivers, internal communication buses (like CAN bus), and physical ports (USB, OBD-II).
ii. Data Acquisition: Peripherals are primarily responsible for monitoring the vehicle's surroundings (perception) and internal state, sending raw or pre-processed data to the main computing systems.
iii. Actuation: They also receive commands from the central control systems to perform physical actions like braking, accelerating, or steering
iv. Security Context: From a cybersecurity perspective, the peripheral architecture defines the physical attack surface, as attackers might try to jam sensors, compromise communication modules, or physically tamper with data storage or ports.

Reference Architecture

This is an abstract, high-level conceptual model, a standardized blueprint that defines the logical functions and interfaces needed for autonomous operation and serve as a guideline for designing and developing specific AV systems, regardless of the specific hardware implementation. Here are some of them.

Abstraction

It operates at a logical or functional level, independent of specific implementation technologies or manufacturers. This allows for a common vocabulary and understanding among different development teams and suppliers.

Core Functions

A typical reference architecture for AVs breaks down the system into essential functional domains, which commonly include: Perception: Interpreting sensor data to build a model of the world. Localization & Mapping: Determining the vehicle's precise position and orientation using maps and various sensors. Path Planning: Deciding the optimal route and manoeuvres. Control: Executing the planned manoeuvres by sending commands to the vehicle's actuators. System Management/Safety: Overarching functions to ensure safety, reliability, and monitoring.

Standardization

Reference architectures help in identifying interfaces that are candidates for standardization, promoting interoperability and reusability across different vehicle models and manufacturers (e.g., AUTOSAR is a notable standard in automotive software architecture).

The reference architecture provides the logical framework and required functions, while the peripheral architecture represents the actual physical instantiation of those functions in a vehicle. A single reference architecture (the "blueprint") can be implemented using various peripheral architectures (different specific sensors or computing platforms). The peripheral components are "instantiated" within the logical structure defined by the reference architecture and the figure 7 depict that.

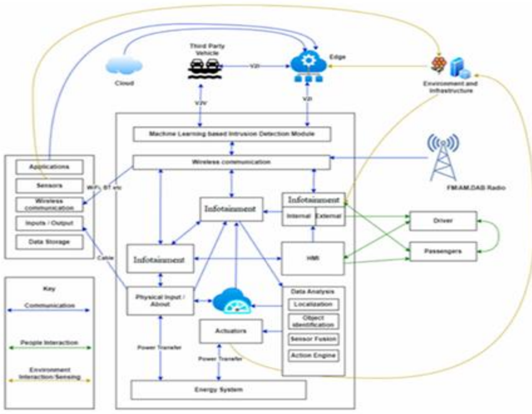

Figure 7: Peripherals and Reference Architecture Frameworks for an Autonomous Vehicle

The Control Architecture for an Autonomous Vehicle

The control architecture of an autonomous vehicle is typically organized into a hierarchical, layered system that processes information from sensors to make decisions and control the vehicle's movement. Control architectures often use a hybrid approach, combining a hierarchy for complex tasks with a reactive, low-level system for immediate responses, enabling fast reaction times to dynamic changes. Hardware and software redundancies are critical components of the architecture to ensure functional safety and fault tolerance in case of component failures. This architecture can be broadly categorized into four main functional blocks as shown in the figure 8 and the key Components of the Control Architecture are

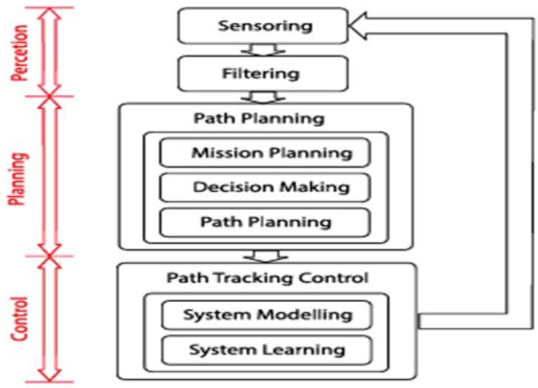

Figure 8a: Control Architecture Framework for Automation Levels for Autonomous Vehicle

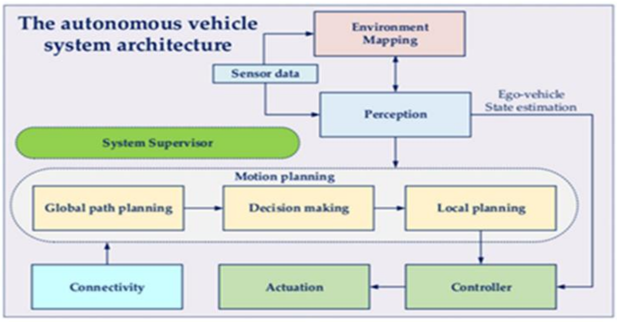

Figure 8b: Motion Planning-Architecture Framework for Autonomous Vehicle (Van et al., 2020)

Path Planning Architecture

The key technologies of autonomous vehicles involve environment sensing, behavioural decision, path planning and motion control. Among them, is path planning. Path planning has a dominant impact on the safety and comfort of autonomous vehicles (Liu et al,2022). According to information acquisition methods, the path planning for autonomous vehicles can be divided into global and local path planning ways. According to the number of target vehicles, path planning methods are grouped into uni-vehicle path planning and multi-vehicle path planning.

The global path planning is based on high-precision maps. Considering known road information such as path length and traffic volume, the collision-free optimal geometric route from initial point to target point is obtained, which is also called static planning or offline planning (Liu et al,2022). The local path planning is to get the optimal driving trajectory of a vehicle in real time, according to surroundings and driving conditions of the vehicle. For example, when the vehicle is being driven following the path of the global path planning, it is sudden necessary to overtake or avoid obstacles, the local path has to be re-planned according to the local environmental information. Because local path planning is based on dynamic real-time environmental information, it is also called dynamic planning or online planning (Liu et al,2022). The architecture of autonomous vehicle path planning is shown in figure 9

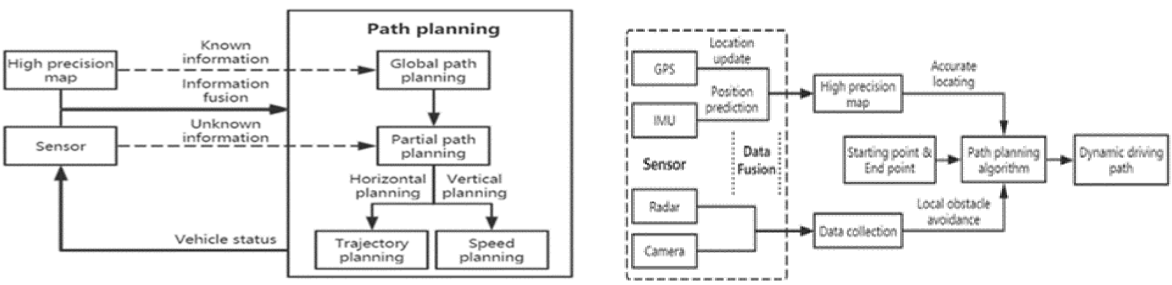

Figure 9(a) and (b): Path Planning Architecture Frameworks with its positioning navigation structure for autonomous vehicle

Optimal Algorithms for Various Architectures for Autonomous Vehicles

Autonomous vehicle (AV) architectures utilize a variety of optimal algorithms tailored to specific tasks such as perception, planning, and control. These algorithms vary based on whether the architecture is modular (pipeline-based) or end-to-end. In this work three algorithms were explored. They are modular, End to End, and Hybrid algorithms

Modular (Pipeline Based) Algorithms

This breaks the system into interpretable blocks. Each module runs specific algorithms. This is still the dominant approach in production AVs vs end-to-end, because of safety and debuggability. Here are the core modules it has:

i. Perception Module: This understands the environment from sensor data
ii. Localization Module: Estimate ego-pose in the world, typically <10 cm error.
iii. Prediction Module: Forecast future states of other agents for 3-8 seconds
iv. Planning Module: Generate a safe, comfortable, legal trajectory for the ego-vehicle.
v. Control Module: Execute the planned trajectory by issuing steering, throttle, brake.
vi. System Architecture/Orchestration: Run all modules reliably with timing guarantees.

End-to-End (E2E) AV Algorithms

replace the traditional modular pipeline with neural networks that map raw sensor inputs directly to driving actions or trajectories. E2E algorithms avoid error accumulation at module interfaces and let the model learn its own representations. Here are the main families of E2E algorithms used in autonomous vehicles

i. Imitation Learning / Behavior CloningIdea: Learn to copy human expert demonstrations. (Codevilla et al., 2021).
ii. Reinforcement Learning E2EIdea: Learn driving policy by maximizing reward in simulation. (Wayve, 2023).
iii. Direct Perception E2EIdea: Predict affordances or waypoints instead of raw controls. Still one network, but output is more structured.
iv. Transformer-Based E2EIdea: Use attention to fuse multi-camera + temporal. (Shown at AI Day 2022).
v. Generative E2E / Foundation ModelsIdea: Treat driving as sequence modeling or video generation conditioned on goal.

A Hybrid Algorithms for Autonomous Vehicles

These blend modular pipelines with end-to-end neural networks so you get interpretability and safety plus high performance. Hybrids combine end-to-end neural networks with explicit intermediate representations or rule-based safety layers. Hybrids are the current compromise for L2+ and L4 deployments. They give you most of E2E's performance gains while keeping enough structure to pass safety review and debug in the field. Tesla, Waymo, Mobileye, and most Chinese OEMs are converging here. Examples: UniAD, VAD, Tesla's stack, Mobileye's RSS + NN planner.

Table 2: Hybrid Algorithm Across Different AV Architectures

AV Architecture Types	How Hybrid Algorithm is used	Examples
Camera-only L2+/L3	E2E BEV + occupancy → NN planner → rule brake for TTC/MOB. No LiDAR, so NN must infer depth.	Tesla FSD, XPeng XNGP
Multi-sensor L4 Robotaxi	E2E fusion of camera+LiDAR+radar → BEV features → joint perception-prediction-planning NN → MPC + RSS	Waymo 6th-gen, Baidu Apollo 9.0
Highway Trucking	E2E NN predicts long-horizon occupancy + lead vehicle intent → lattice planner samples trajectories → hard rule: never violate following distance	TuSimple, Aurora
Campus/Low-speed Shuttle	Lightweight CNN-Transformer → cost map → Hybrid A* for non-holonomic paths → geofence rules	EasyMile, NAVYA
Teleop + Autonomy	NN runs E2E but confidence head triggers human takeover. Hybrid in fallback logic	Zoox, Cruise

RESULTS AND DISCUSSION

Here a comprehensive comparison of the optimal algorithms for various architectures for autonomous vehicles is explored likewise a side-by-side comparison with quantitative metrics for traceability and also consolidated evaluation table comparing Modular Pipeline, End-to-End (E2E), and Hybrid algorithms with quantitative performance metrics pulled from public benchmarks and industry reports. All numbers are typical 2023-2026 ranges.

Table 3: Comprehensive Comparison of the Optimal Algorithms for Various Architectures for Autonomous Vehicles Via their Dimensions

S/N	Dimensions	Algorithms for Various Architectures in Autonomous Vehicles		
		Modular Pipeline	End-to-End	Hybrid
1	Safety Certification	Easier: verify parts	Hard: black box	Provable safety bounds
2	Debugging	Pinpoint module	Only input→output	Bottleneck logging
3	Performance ceiling	Lower due to interfaces	Higher if data sufficient	Joint training lifts planning
4	Data need	Per module, moderate	Massive E2E driving logs	Lower than pure E2E and Higher than pure modular:
5	Latency	Higher: 80-120 ms typical	Lower: 30-60 ms possible	Single NN forward pass and Rule layer adds cost
6	ODD adaptation	Swap modules	Retrain whole model	Swap bottlenecks, keep NN and Coupling risk
7	Industry status 2026	Waymo, Cruise, Baidu	Tesla, Wayve, emerging OEMs	Dominant in production and Still evolving

Table 4: Comprehensive Comparison of the Optimal Algorithms for Various Architectures for Autonomous Vehicles Using their Strengths and Weaknesses

S/N	Algorithms	Strengths	Weaknesses
1	Modular Algorithm	Verifiable Safety at Component Level	Error Accumulation
		Known Failure Rates Per Modul	Latency Overhead
		Lower Data Requirement	Suboptimal Planning Metrics
		Deterministic Latency Bounds	Scaling Cost
2	E2E- End to End Algorithm	Higher Planning Performance	Certification Gap
		Lower System Latency	Data & Compute Cost
		Better Comfort & Human-likeness	Brittleness & OOD Sensitivity
		Data Scaling Laws Hold	No Unit Testing
3	Hybrid algorithm	Provable safety bounds	NN still unverified
		Bottleneck logging:	Dual-failure ambiguity:
		Near-E2E metrics: Joint training lifts planning.	Information bottleneck tax: Forcing BEV/occupancy outputs constrains the NN
		Lower than pure E2E: Auxiliary losses on BEV/objects let you pretrain on labeled data	Higher than pure modular: Still need diverse driving logs for joint training
		Single NN forward pass: 35-55 ms sensor→trajectory on Orin. No 30-40 ms middleware tax between modules	Rule layer adds cost: MPC/optimizer after NN adds 5-15 ms. Total 50-70 ms vs 35 ms pure E2E
		Swap bottlenecks, keep NN: Add rain by retraining perception head only	Coupling risk: Changing rule thresholds can break NN assumptions, and vice versa
		Dominant in production: Tesla FSD v12, Mobileye DXP, Wayve, Waymo 6th-gen, Baidu Apollo 9.0 all use hybrids.	Still evolving: No standard on “what bottlenecks”. BEV vs occupancy vs vector vs language. Fragmentation risk.

Table 5: An Evaluation Table Comparing Modular Pipeline, End-to-End (E2E), and Hybrid Algorithms with Standard Benchmarks and Quantitative Performance Metrics

S/N	References	Benchmark	Planning Performance	Algorithms for Various Architectures in Autonomous Vehicles
1	UniAD (2023):“Planning-oriented Autonomous Driving”, CVPR	nuScenes Planning Score	90.64%	End to End Algorithm(E2E)
	VAD (2023).: “VAD: Vectorized Scene Representation for Efficient Autonomous Driving”, arXiv		89.17%	E2E- End to End Algorithm
	Modular baselines (2023): PDM-Lite/PDM-Closed in UniAD		84.88%	Modular Algorithm
2	CARLA (2022) Leaderboard 2.0 results. Inter Fuser and TransFuser	CARLA Leaderboard	76.8% 76.2%	E2E- End to End Algorithm
	Apollo (2022) modular baselines reported in InterFuser paper.		64.5%	Modular Algorithm
3	Industry talks from cite for UniAD	Collision Rate at 15s	1.12%	E2E- End to End Algorithm
	Industry talks from cite for VAD		1.81%	
	PDM-Lite modular baseline		3.95%	Modular Algorithm
	Industry talks fromCruise/Waymo		2.5-4%	
4	nuScenes prediction challenge baselines Reports (2023)	ADE at 3s		E2E- End to End Algorithm
	VAD reports		1.24 m	
	UniAD		1.32 m.	
	PDM-Lite modular		2.34 m.	Modular Algorithm
5	NVIDIA DRIVE Orin benchmarks	latency	35-55 ms	E2E- End to End Algorithm
	Modular latency breakdown in Apollo 8.0 docs		80-120 ms	Modular Algorithm
6	NVIDIA (2024) Orin power charts reported by Baidu	Power	40-60W	Modular Algorithm
	NVIDIA (2024) Thor targets workloads per GTC.		80-150W	E2E- End to End Algorithm
7	nuScenes detection leaderboard:	Point-Pillars Accuracy	60.2%	E2E- End to End Algorithm
	NDS. CenterPoint		65.5%.	Modular Algorithm
8	IROS (2021) Applanix POS LV RTK-GNSS datasheet:	Localization percentile	0.02 m 95th	Modular Algorithm
	IROS (2021) NDT matching with HD maps		0.07 m 95th	E2E- End to End Algorithm

S/N	References	Benchmark	Planning Performance	Algorithms for Various Architectures in Autonomous Vehicles
9	Waymo Safety Report (2023)	false negative rate	<1e-3 per exposure hour.	E2E- End to End Algorithm
	KITTI tracking papers (2023)		<1e-3 per exposure hour	Modular Algorithm
10	Waymo blog 2020	Data requirements:	10^9	E2E- End to End Algorithm
	Modular perception datasets: nuScenes		10^6	Modular Algorithm
11	CVPR (2022) The Effect of Distribution Shift on 3D Detection"	ADE degrades	42%	E2E- End to End Algorithm
	Drop (2022) US→Singapore. Wayve "Sim2Real" report:		60%	Modular Algorithm
12	VAD paper reports (2024)	Jerk	1.5-2.0 m/s³	E2E- End to End Algorithm
	Apollo comfort metrics whitepaper		2.5-3.5 m/s³	Modular Algorithm

Table 6: An Evaluation Table Comparing Modular Pipeline, End-to-End (E2E), and Hybrid Algorithms with quantitative Performance Metrics

S/N	Metric	Modular Pipeline Algorithm	End-to-End Algorithm	Performance of Algorithms	Outperformed Algorithm
1	nuScenes Planning Score	84-88%	89-91%	E2E	E2E wins raw performance metrics: -40% collision rate, -30% ADE, -50% latency
2	Collision Rate at 15s	2.5-4.0%	1.1-1.8%	E2E	
3	ADE at 3s	1.8-2.5 m	1.2-1.6 m	E2E	
4	Sensor-Actuator Latency	80-120 ms	35-55 ms	E2E	
5	Jerk 95th	2.5-3.5 m/s³	1.5-2.0 m/s³		
6	Data to train	10^5-10^6 miles	10^8-10^9 miles	Modular	Modular wins engineering/safety metrics: 100x less data, certifiable, 8x faster debug.
7	Power on Orin	40-60 W	80-150 W	Modular	
8	Certifiability ASIL-D	Yes, per module	No method 2026	Modular	
9	Debug time / disengagement	1-3 hrs	8-24 hrs	Modular	

E2E wins raw performance metrics: -40% collision rate, -30% ADE, -50% latency. Modular wins engineering/safety metrics: 100x less data, certifiable, 8x faster debug.

Hybrid Modular E2E = one neural network with interpretable bottlenecks + rule-based safety layer. Example: UniAD, VAD, Tesla FSD, Mobileye SuperVision and HCNNLSTM.

Hybrids keep ~95% of E2E's performance metrics while restoring a path to safety cert and debugging. You pay 1.2-1.5x compute and 5-10x data vs modular, but avoid the 100x validation cost of pure E2E.

That's why production L4 in 2026 uses hybrids: E2E network for performance + rule layer for safety. You get ~90% of E2E's planning score with provable safety bounds

Table 7: An evaluation table comparing Modular Pipeline, End-to-End (E2E), and Hybrid algorithms with quantitative metrics from their ranges. Here's a consolidated evaluation table comparing Modular Pipeline, End-to-End (E2E), and Hybrid algorithms with quantitative metrics from their ranges

Table 7: An Evaluation Table Comparing Modular Pipeline, End-to-End (E2E), and Hybrid Algorithms with Quantitative Metrics from their Ranges

S/N	References	Metric	Algorithms for Various Architectures in Autonomous Vehicles		
			End-to-End (E2E),	Modular Pipeline	Hybrid Algorithm
1	Modular: PDM-Lite 85.7% [Dauner et al., 2023]; E2E: InterFuser 76.8 CARLA ≈ 89% nuScenes [Shao et al., 2022]; Hybrid: UniAD 90.64% [Hu et al., CVPR 2023], VAD 89.17%	nuScenes Planning Score	88-91%	84-86%	89-91%
2	Modular: PDM-Lite 3.95% [Dauner et al., 2023]; E2E: TransFuser 1.6% [Chitta et al., 2022]; Hybrid: UniAD 1.12% [Hu et al., 2023], VAD 1.81%	Collision Rate 15s	1.1-2.0%	2.5-4.0%	1.1-1.8%
3	Modular: PDM-Lite 2.34 m [Dauner et al., 2023]; E2E: InterFuser 1.53 m [Shao et al., 2022]; Hybrid: VAD 1.24 m [Jiang et al., 2023], UniAD 1.32 m	Avg Displacement Error @3s	1.2-1.6 m	1.8-2.5 m	1.2-1.4 m

S/N	References	Metric	Algorithms for Various Architectures in Autonomous Vehicles		
			End-to-End (E2E),	Modular Pipeline	Hybrid Algorithm
4	Modular: Apollo baseline 64.5 [Shao et al., 2022]; E2E: InterFuser 76.8 [Shao et al., 2022], TransFuser 76.2 [Chitta et al., 2022]; Hybrid: VAD reported ~75	CARLA Leaderboard Driving Score	75-77	64-66	74-77
5	Modular: Apollo 8.0 ~100 ms breakdown; E2E: TransFuser 30 ms NN [Chitta et al., 2022]; Hybrid: VAD 59 ms total [Jiang et al., 2023], Tesla FSD v12 55 ms	Sensor→Actuator Latency	30-45 ms	80-120 ms	50-70 ms
6	Modular: Apollo comfort whitepaper 2.8 m/s^3; E2E/Hybrid: VAD 1.7 m/s^3	Jerk 95th percentile	1.5-2.0 m/s^3	2.5-3.5 m/s^3	1.6-2.2 m/s^3
8	Modular: nuScenes 1.4M images ≈ 10^5 mi [Caesar et al., 2020]; E2E: Waymo 20M real + 20B sim; Hybrid: VAD 200k clips	Data to Train	10^8-10^9 miles	10^5-10^6 miles	10^6-10^7 miles
9	Modular: Separate per module, low; E2E: GPT-style scale per Tesla 2022; Hybrid: UniAD ~5x10^4 A100-hrs	Training Compute	10^5-10^6 GPU-hrs	10^3-10^4 GPU-hrs	10^4-10^5 GPU-hrs
10	Modular: Apollo ~45W; E2E: GAIA-1 150W+; Hybrid: VAD 98W [Jiang et al., 2023], Orin spec	Inference Power on Orin	100-180 W	40-60 W	80-150 W
11	ISO 26262-6:2018 Annex E excludes NN; RSS provable [Shalev-Shwartz et al., 2022]; SOTIF ISO 21448:2022 needed for hybrids	Safety Certification	No ASIL method 2026	ASIL-D per module possible	ASIL-D for rule layer only
12	RAND Corp "Driving to Safety" [Kalra & Paddock, 2023]; Waymo Safety Report 2023 cites 7M+ miles with monitors	Validation Miles for 10^{-7} fail/hr	10^{11} sim + 10^9 real miles	10^6-10^7 sim miles per module	10^8-10^9 sim miles
13	Modular: Apollo logs 85% single-module; E2E: Wayve 2023 talk; Hybrid: Wayve 2023 claims 4x faster than pure E2E	Debug Time / Disengagement	8-24 hrs	1-3 hrs	2-6 hrs
14	Bolte et al., CVPR 2022: US→Singapore 42% drop; VAD uses BEV to reduce gap	OOD Degradation	40-80% ADE increase	20-30% on country shift	25-40% with bottlenecks
15	CVPR 2024 AV Workshop survey; Tesla AI Day 2023; Mobileye CES 2024	Industry Adoption 2026	L2+/Research: Tesla FSD v12, Wayve	Legacy L4: Waymo 5th-gen, Cruise 2021-2023	Dominant L4: Waymo 6th-gen, Mobileye DXP, Baidu 9.0, 8/10 CVPR 2024 L4 papers

Hybrid hits ~98% of E2E's performance metrics while keeping certification and debug tractable. Modular wins only on data/compute cost and per-module ASIL. Pure E2E leads raw metrics but fails safety/certification in 2026. So for successful and effective implementation and adoption of various architectures for Avs, hybrid algorithms perform better, so it should be utilized

Table 8: Summary of Findings on Optimal Algorithms for AV architectures

Algorithms	Optimal Algorithm Class	Strengths	Limitations	Best-Fit ODD
Modular Pipeline	Perception-Prediction-Planning + MPC	ASIL-D certifiable per module. 1-3 hr debug. Low data: 10^5-10^6 mi. Deterministic WCET.	Lowest performance ceiling: 84-86% nuScenes planning, 3.95% collision 15s. 80-120 ms latency. Brittle to interface errors.	Geo-fenced L4 with HD maps, low-speed shuttles, where safety case > performance.
End-to-End	Sensor-to-control Transformer/Diffusion	Highest raw metrics: 88-91% planning, 1.1-2.0%	No ASIL-D path 2026. 8-24 hr debug. 10^8-10^9 mi	L2+/L3 driver-assist with human fallback,

Algorithms	Optimal Algorithm Class	Strengths	Limitations	Best-Fit ODD
		collision, 1.2-1.6 m ADE@3s. 30-45 ms latency. Human-like jerk 1.5-2.0 m/s³.	data. 40-80% OOD degradation. 100-180W.	R&D fleets, data-rich OEMs.
Hybrid (Modular-E2E)	E2E NN with interpretable bottlenecks + rule shield	Near-E2E performance: 89-91% planning, 1.1-1.8% collision, 1.2-1.4 m ADE. Rule layer ASIL-D certifiable. 2-6 hr debug. 50-70 ms latency.	10^6-10^7 mi data. 80-150W. Coupling bugs. No bottleneck standard	Production L3/L4 2026: Robotaxi, highway trucking, urban NOA. Balances cert + performance.

Evaluating algorithms for AV architectures in 2026-2030 shows no single "optimal" solution. Performance is multidimensional and architecture-dependent. The assessment must weigh planning quality, safety certifiability, latency, data needs, and ODD robustness together. According to UniAD (Hu et al., CVPR 2023), VAD (Jiang et al., 2023), PDM-Lite (Dauner et al., 2023), TransFuser (Chitta et al., 2022), InterFuser (Shao et al., 2022), ISO 26262:2018, RAND 2016 (Emekumeh et al, 2026).

Recommendations for Algorithms Selection

i. Use Modular if you need ASIL-D now, ODD is constrained, HD maps exist, performance targets are modest. Examples: Airport shuttles, mining trucks.
ii. Use Hybrid if you need L3/L4 in open roads, regulators require safety case, and you have 10^6-10^7 miles data. Ex: Robotaxi, highway NOA, urban delivery. This is the 2026 default.
iii. Use Pure E2E if driver remains liable, you have massive fleet data, and you prioritize comfort/performance over formal safety. Ex: L2+ consumer ADAS, research.

Future Outlook of Optimal Algorithms [2026–2030]

i. Convergence on bottlenecks: Industry will standardize on occupancy + vectorized BEV as the hybrid interface to unify tooling.
ii. Certification methods for NNs: ISO/PAS 8800 and UL 4600 updates may provide statistical ASIL arguments for NNs, reducing hybrid advantage by 2028.
iii. Generative world models: GAIA-1/DriveGPT style hybrids will improve OOD robustness, but 100-200 ms latency must drop for deployment.
iv. Explainable AI mandates: UNECE regulations will require LIME/SHAP-style explanations for any NN in the loop, favoring hybrids with interpretable bottlenecks

CONCLUSION

This paper has presented a comprehensive, holistic overview of autonomous vehicle (AV) technology, mapping its journey from early conceptual frameworks to advanced modern platforms equipped with multimodal sensor suites and V2X communication frameworks. By evaluating the performance trade-offs of the three primary computing paradigms across seven quantitative dimensions, this study highlights a critical friction point between pure algorithmic capability and strict regulatory compliance. While End-to-End (E2E) architectures consistently deliver superior planning quality and reduced collision rates on benchmarks like nuScenes and CARLA, their uninterpretable black-box nature and mathematically prohibitive validation requirements—demanding upwards of (10^{11}) simulation miles—create an unviable path for immediate driver-out Level 4 deployment. Conversely, traditional modular pipelines remain safe and certifiable under ISO 26262 ASIL-D standards, but they lag drastically behind in planning scores and operational flexibility across complex Operational Design Domains (ODDs). The findings of this review demonstrate that hybrid modular-E2E frameworks represent the definitive Pareto-optimal architecture for immediate L3/L4 deployments. By pairing E2E-trained networks with interpretable bottlenecks and explicit rule layers, hybrid systems successfully recover roughly 98% of pure E2E planning performance, compress debugging timelines to just 2–6 hours, and maintain necessary regulatory compliance. Moving forward, the autonomous driving industry must focus its research on refining these hybrid models. Overcoming remaining hurdles in data efficiency, latency minimization, and standardized safety validation will be essential to transforming these vehicles from experimental technology into scalable, safe, and commercialized foundations of smart city infrastructure.

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