# From Automated to Autonomous Vehicles: An Analysis of SAE Levels and Agentic AI

HENSSEL STEPANEK, MONICA LEBA, ANDREEA IONICA
University of Petrosani,
Petrosani,
ROMANIA

*Abstract:* - The creation of more advanced autonomous driving systems has made problems with perception, planning, adaptation, and decision-making in variable driving environments more significant. In response to these challenges, Agentic AI is an artificially intelligent system that is capable of autonomous, purposeful behavior through reasoning and environment interaction; it is adaptive and goal-directed. This paper investigates the relationship between the SAE J3016 levels of driving automation and the capabilities commonly associated with Agentic AI. First, a literature review is conducted to examine the evolution of autonomous vehicles, the SAE automation framework, and the fundamental concepts of Agentic AI. Representative driving scenarios and general functional architectures are then presented using the CARLA simulator and conceptual diagrams to illustrate the characteristics of the different SAE automation levels. A conceptual comparison was conducted to understand how the functional requirements of evolving levels of vehicle automation relate to Agentic AI characteristics. The characteristics become more relevant at higher levels of SAE automation, particularly at levels 4 and 5, where automation provides more autonomy, reasoning, and makes plans and decisions based on adaptability. The report also looks into the hardware and circuit-level enablers of this transition, as well as computing architectures, multi-sensor fusion hardware, and representative vehicles of automotive embedded computing and their respective levels of SAE automation. The study presents a conceptual view of Agentic AI on future autonomous driving systems and offers suggestions for future studies.

*Key-Words:* - Agentic AI; Autonomous Vehicles; SAE J3016; Driving Automation; Automated Driving System (ADS); CARLA Simulator; Decision Making.

Received: April 28, 2026. Revised: June 29, 2026. Accepted: August 9, 2026. Published: November 23, 2026.

## 1 Introduction

This paper investigates the correlation between SAE levels of driving automation and Agentic AI. The increasing levels of driving automation shift the responsibilities of the Automated Driving System (ADS) to perceive, decide, plan, and adjust to changing driving conditions. Driving an increasingly automated vehicle involves a degree of Agentic AI in that it involves autonomously reasoning, goal-directed behavior, and adaptive decision making.

We review the state of autonomous vehicles, the SAE driving automation levels, and the foundations of Agentic AI. We review various driving scenarios to illustrate the characteristics of the SAE automation levels. We then discuss the requirements of the functionality of event higher levels of automation, and how close these requirements are to Agentic AI.

The most important contribution of this research is the comparison of the progression of the SAE levels of automation to the Agentic AI framework. We examine how higher levels of vehicle automation introduce increasingly demanding requirements for perception, decision making, planning, and adaptation, and how these requirements correspond to the capabilities commonly attributed to Agentic AI. The representative driving scenarios and functional architectures presented in this work illustrate the differences between the various SAE automation levels and support the conceptual discussion presented in this paper.

In addition to this conceptual comparison, this paper examines the hardware and circuit-level foundations that make Agentic AI computation feasible within the strict latency, power, and thermal constraints of automotive systems. We review specialized computing architectures, including Graphics Processing Units (GPUs), Field-Programmable Gate Arrays (FPGAs), Application-Specific Integrated Circuits (ASICs), and

neuromorphic processors, together with the circuit-level challenges of real-time multi-sensor fusion, and we map representative embedded automotive computing platforms against the SAE automation levels to illustrate how compute and power budgets scale with increasing automation.

## 2 Literature Review

### 2.1 Evolution of Autonomous Vehicles

Gradually over the past century, vehicles have been able to drive themselves more and more. The idea for controlling vehicles remotely first gained some traction in the first half of the 20th century. The first documented case was in 1921 when a vehicle was operated remotely without the driver onboard. Radio-controlled vehicles were followed by the use of invisible beams for transportation. The first half of the 20th century spawned many interesting ideas for driverless vehicles from engineers and university researchers. In the 1980s both university and industrial research for driverless vehicles exponentially increased. The Pro-Methues project at Mercedes-Benz drove a robotic car on a busy freeway around greater Paris in 1994 [1].

Increased traffic, more accidents, and advancements in technology created interest in automating vehicles. The design of driverless cars improved the transport system with the goal of being safer and more efficient. It became clear that driverless systems needed an extensive technological support system. When the supporting systems were completed, driverless systems were able to utilize advanced safety and navigation technologies. The foundation of modern autonomous transportation was complete with the completion of these supporting systems, [1], [2].

The first accepted technology for driver assistance was Cruise Control. This technology added the ability for vehicles to drive at a constant speed without the driver having to assist or control speed. This technology was the first of its kind to begin to allow drivers to control or drive at a task instead of a function. Although somewhat limited, Cruise Control laid the groundwork for what was to come next. Limitations were broken with Adaptive Cruise Control (ACC). ACC brought environmental awareness and controlled speed adjustment based on traffic. This was the first step towards Advanced Driver Assistance Systems (ADAS) and higher levels of driving automation [3].

ADAS Systems show how we are moving toward various levels of automation in vehicles with an even higher level of safety. Each system integrates one or more safety components, including cameras, sensors, radar, and advanced control systems and assists the driver in one or more driving functions. In particular, Advanced Driver Assistance Systems assist the driver in numerous tasks related to the driving task. Their use is rapidly increasing in the development of automated and even autonomous vehicles. It is obvious that the use cases of ADAS drive the automation of functions and tasks historically done by the driver. The report State of ADAS, Automation, and Connectivity produced by the Center for Automotive Research, demonstrates how ADAS technology is evolving from early stages of the technology, like vision enhancement and function augmentation to provide warnings and perform task automation of functions to assist the driving task.

One of the more common ADAS technologies offered is Lane Keeping Assist Systems (LKA). LKA uses a camera or vision system to identify lane marks and/or painted lines. LKA works by maintaining the vehicle in the lane of travel. LKA systems are designed to warn the driver through the use of visual or audible cues when an unintended lane departure is detected and in some systems, will assist the driver by control intervention. LKA technologies increase safety and decrease the workload of driving, especially on long, monotonous highways [3].

ACC introduces a level of environmental awareness into an existing Cruise Control function through the use of sensors to monitor the flow of the traffic around the vehicle. Unlike standard Cruise Control where speed is preset and the vehicle is more or less locked into that speed, ACC is able to adjust the speed to ensure each vehicle is kept a safe distance away from the next. This leads to more comfortable driving and minimizes the effort and stress involved, particularly on slow and congested highways. It is considered one of the first and most important ADAS technologies to pave the way for an advanced automation of the driving process [3].

Automatic Emergency Braking (AEB) is an Advanced Driver Assistance System (ADAS) designed to recognize hazardous situations in the driving environment and can autonomously engage the brakes to mitigate collisions. AEB can prevent or lessen the severity of collisions by engaging the brakes faster than the driver is able. Because of this, AEB systems are recognized as one of the top safety features of modern commercial vehicles and are credited with significant collision reductions for advanced driver assistance systems [3].

As autonomous driving began to materialize, significant advancements in sensing technology

became a prerequisite for the development of autonomous driving systems. Monitoring the environment is a critical building block of autonomous driving. Modern autonomous driving systems use cameras, radars, lidars, GPS, inertial measurement units, and ultrasonic sensors Among many others. These technologies provide information on the physical characteristics of the roads, the presence of vehicles on the road, the potential obstacles, and the ambient driving conditions, respectively [2], [4].

In the context of driving automation, AI makes critical driving decisions by processing sensor outputs. Autonomous driving systems integrate environmental perception, position, route selection, and decision-making functions. AI, coupled with machine learning and deep learning, largely dominate critical functions, such as environmental perception and decision-making AI and are the most important technologies for autonomous driving [4].

Autonomous vehicles now utilize integrated systems of state-of-the-art sensors, sophisticated AI and computer systems, and powerful processing and control systems. Autonomous Driving Systems are now capable of understanding and interpreting various environments, making driving decisions, and controlling the motion of the vehicle in more intricate and complex environments. More advanced systems can accurately detect and classify objects in diverse environments, predict the behaviors of other agents, and dynamically derive routes to optimize safety and efficiency of the journey. Emerging technologies of autonomous driving amend safety and accessibility issues of modern transportation while enabling the construction of futuristic Smart transportation systems. As of now, different stages of driver-assist systems are transitioning to higher automated and fully autonomous systems. An easing of proprietary and open-source constraints has allowed for rapid advancement of new systems, as well as collaborative research within the automotive space [2], [4].

## 2.2 SAE Levels of Driving Automation

The J3016 standard from the Society of Automotive Engineers (SAE) describes requirements for level classification of driving automation systems to help identify the level of automation that enables necessary human engagement for safe driving. The standard defines six levels of driving automation systems. These cover the range from Level 0 (No Driving Automation) to Level 5 (Full Driving Automation). The Level designations describe the allocation of the driving task between the driver and the driving automation system. This involves the control of the vehicle, monitoring the environment, and making decisions. The SAE classification defines Level 0 as a driving task where the driving automation system is not present, and the driver performs all the driving task requirements. Level 1 introduces driver assistance functions that support either longitudinal or lateral control of the vehicle, but not both, simultaneously. Level 2 offers sustained lateral and longitudinal control of the vehicle under certain operating conditions, while the driver remains responsible for managing the driving environment and intervenes when necessary. [4], [5].

Level 3 of automated vehicle classification is defined as Conditional Driving Automation, where the system performs the complete task of dynamic driving within a specific Operational Design Domain (ODD). While the system performs the driving task, the driver must stay 'ready' to take over driving, if prompted to do so by the driving automation system. Level 4 Driving Automation includes automation of the complete driving task and automation of fallback maneuvers in the Operational Design Domain, which may require intervention by the driver. Level 5 Driving Automation is the highest classification in automated vehicles and includes Full Driving Automation, where the vehicle is capable of driving itself under any roadway, environmental or traffic conditions, and does not require the intervention of a human operator [4], [5].

Although SAE J3016 is the most widely adopted standard for classification of vehicle automation levels, researchers have indicated limitations of the standard. One major concern is the low consideration given to ODDs in the standard. ODDs provide the operational and environmental contexts of the automated driving system domain. Systems classified at the same SAE level may have the ability to operate under drastically different conditions, leading to problems with making fair comparisons. This may be attributed to the systems being designed to achieve tasks of varying levels of automation or complexities [6], [7].

Because the SAE framework defines the distribution of driving responsibility between the human and the automated systems, the rest of the framework describes the boundaries and typing of driving technologies in somewhat abstract terms. Automated systems defined at the same automation level may present very different operating conditions and capabilities. Thus, many researchers consider the SAE automation levels (Table 1) to qualitatively describe automated systems in an incomplete manner, as they address peripheral

factors such as operational contexts and human-machine engagement to a very small degree [6], [7].

Table 1. SAE Levels of Driving Automation

| SAE Level | Description | Driver Responsibility |
|---|---|---|
| **Level 0** | No Driving Automation | Full control and environmental monitoring |
| **Level 1** | Driver Assistance | Driver monitors the driving environment |
| **Level 2** | Partial Driving Automation | Driver monitors the driving environment and remains ready to intervene |
| **Level 3** | Conditional Driving Automation | Driver must remain receptive to a request to intervene issued by the automated driving system |
| **Level 4** | High Driving Automation | No driver intervention required within the defined ODD |
| **Level 5** | Full Driving Automation | No human involvement required under all driving conditions |

*Source: created by the authors*

Also, the decomposition of driving automation into levels fosters the view that increasing automation levels consecutively builds the foundation toward complete automation. In fact, developing automated technology for vehicles follows many different paths depending on regulatory constraints, the operational context, and other factors. Thus, some of the more advanced technologies of the future that operate on land may never reach Level 5 automation within the mobility domain. Additionally, many have questioned whether it is even useful to achieve, or if it is possible, complete automation of driving in several different contexts, and if there is a need for doing so [6], [7].

Several studies pointed out how the SAE classification system adds confusion in understanding the faults of automated driving systems. This is particularly evident in the area of public perception. Some studies show that firms choose their terminology to describe their driving systems which influence the perception of drivers and unrealistic expectations of system limits and safe usage [8].

This is prevalent in Level 2 systems. Teoh studied how the various systems affect the perception of drivers. In particular, "Autopilot" systems encourage drivers to believe that the system allows for the performance of various tasks other than driving, or peripheral activities, which is unsafe, as continuous focus is still required [8].

Level 3 is also similarly criticized. Inagaki and Sheridan said that the SAE definition of Conditional Driving Automation relies on the belief of the drivers to quickly regain awareness and safely take control of the vehicle. In the event of a takeover request, the authors believe it is completely unrealistic to expect that the driver returns to a 'cues ready' state while they are uninvolved in the driving process and performs the requested fallback action [9].

The levels of automation have also received criticism. For instance, Stayton and Stilgoe observe that, in the context of automated vehicles, the SAE J3016 levels of automation show increasing autonomy and define the primary measure of progress. They also provide little insight into the operational and design constraints and considerations that influence the deployment of automated systems. They advocate a shift in focus from the levels of automation to the design of automation systems that operate within known constraints, limitations, and operational design domains, as well as actual examples to illustrate their potential use [6], [7].

## 2.3 Agentic AI Concepts

Artificial Intelligence (AI) advances have been rapid and impressive over the last couple of decades. AI has evolved from rule-based expert systems to advanced machine learning and deep learning models. Traditional AI systems are designed to function in the boundaries of predefined tasks capture by rules and structured data. In domains of relatively focused tasks, these systems can be extremely efficient. However, they lack flexibility to follow open-ended instructions in unpredictable environments. Agentic AI expands the horizon of AI by enabling systems that can act with autonomy, and can be instructed to achieve a set of ambitious goals and objectives, [10].

In the context of AI advances, Agentic AI introduces a new dimension to the field by focusing on systems that can achieve complex goals that require relatively less human prompting, and systems that can operate in flexible and unstructured environments. Agentic AI systems can perceive and act on the environment in which they operate. These systems can reason about their environment and take action, and can learn from experience. Agentic AI systems integrate reasoning, planning, and interaction with a learning memory, and can autonomously function in complex and uncertain environments, [11], [12].

This new era of AI is moving us away from using AI systems to assist us in making decisions;

and toward using AI systems to manage, coordinate and optimize tasks without our active participation. Recent new generations of large language models, tools and methods of reinforcement learning, and architectures of multi agent systems and intelligent decision-making systems have accelerated the development and use of Agentic AI in many diverse sectors of society, [10].

Agentic AI is most recognizable for its high degree of autonomy. Autonomous agents can self-execute a sequence of behavior to achieve a goal without (or with very little) human supervision or interference. These systems learn to adjust and select most appropriate behavior through environmental interaction and assessment of available options. This ability helps Agentic AI excel in situations where rapid responses and continual adjustment to new environments is necessary [10], [11].

Agentic AI systems are intended to modify their behavior to fit the new demands of the ecosystem in which they operate. In contrast to most conventional AI systems, which are built upon a firm set of rules, Agentic AI systems learn through interactions and adjust their behavior via feedback, allowing them to sustain optimum performance within a volatile environment even when the conditions that are present differ from those of the AI system's training. [10], [11].

The “agentic” aspect of Agentic AI stems from its inherent goal-directedness. Agentic systems do not rely on the input-output model. They are intended to be highly self-directed in the achievement of sequences of behavior in the pursuit of complex, self-determined goals. Agentic systems are capable of making sophisticated, context-sensitive decisions and of coordinating multiple activities that will help them accomplish their goals, [11].

Agentic AI systems need planning to break down complex tasks into a series of sequential sub-tasks. Planning helps an agent evaluate different strategies and decide on the proper action to attain its goal. Planning becomes necessary when the environment exhibits dynamism, in which case decisions must consider a range of goals and the flexibility to model interactions among multiple stakeholders that can change [11], [12].

Decision Making involves Agentic AI systems weighing the available information and environmental conditions and determining the optimal course of action toward the defined objective. Perceptive agentic systems are capable of integrating planning and learning in order to evaluate alternative courses of action and predict their outcomes in order to choose the path of action that is most likely to help them achieve their defined goal [11].

The transportation sector is one of the primary larger sectors that will benefit from Agentic AI. Autonomous vehicles are designed to perceive their surrounding environment continuously and make decisions and plans to avoid obstacles and drive along the optimum route while continuously thinking about and reacting to other vehicles on the road. Agentic AI will allow vehicles to solve complex driving scenarios that change, and to make decisions in real time that improve safety and enhance the efficiency of traveling. Autonomous driving systems are moving towards architectures of integrated advanced software that combines perception, planning, decisions and control [1], [3], [11].

In manufacturing and industry, Agentic AI is increasingly used for intelligent automation of processes in production and for the management of supply chains. Agents are able to monitor processes, allocate resources, adapt to changes and support intelligent automated decisions with minimal human interaction. Furthermore, they can help achieve operational excellence and reduce costs within Industry 4.0 [10].

Healthcare is another field that may benefit from using Agentic AI. Agents can enhance medicine across numerous intersecting fields including diagnosis, treatment, and the management of patient data and clinical support. Agentic AI may help provide more personalized and effective care by continuously processing large volumes of medical information and adapting to patient-specific conditions. Current AI systems are focused on enhanced efficiency of healthcare operations while helping to improve decision making in clinically relevant areas and outcomes as well [10], [11].

## 2.4 Agentic AI and Autonomous Vehicles

Autonomous driving technology has advanced beyond traditional modular architectures [4]. Now one can talk about systems that can reason, plan, and decide for themselves. Agentic AI consists of such systems. It can perceive, plan, act, and learn. Agentic AI systems can also flexibly operate in dynamic environments as contrasted to other AI systems built for narrow tasks [10], [11].

The main research directions of Agentic AI are focused on integrating more sophisticated reasoning mechanisms, reinforcement learning, tool usage, memory systems, and multi-agent coordination. In addition, the research on Agentic AI continues with the goal of finding out how an agent can interact

with its environment, learn from feedback, and improve its decisions through planning and reflection [10], [11].

Developing, training, validating, and testing of different autonomous systems has become much easier with the introduction of realistic simulation platforms such as CARLA [13], [14]. The research community will be able to perform extensive experiments on ordinary and even on rare and safety critical scenarios of urban environments that would be prohibitively expensive and potentially dangerous to create in real life [13]. In addition to basic CARLA, some recent research platforms have been designed to enable multiple, competing autonomous driving agents in user-controlled and varied environments [15].

Agentic AI has the potential to give autonomous vehicles the ability to analyze situational information with greater context using information from cameras, LiDAR, radar, and V2X systems. For example, agentic AI has the ability to learn from and adapt to countless interactions with the environment and can recognize traffic participants and interpret alterations in the environment. Navigation can be made safer and more precise with the use of an agentic AI system in urban environments [10], [11], [14].

Agentic AI is particularly adept at the formation and execution of multi-step plans. In the context of autonomous driving, agentic AI can assist in everything from route planning to obstacle avoidance and lane-changing maneuvers to navigate a more intricate network of traffic. Instead of waiting for the next sensor input, an agent can evaluate several possible actions and choose the best driving strategy according to the context and the long-term goal [11], [12].

Agentic AI has the potential to evaluate changes to the environment and provide real-time decisions based on its learning and adaptive behavior. Adaptive and real-time decision-making can provide the needed flexibility to deal with unfamiliar road conditions, unpredictable road users, adverse weather, and unanticipated road changes. Agentic AI can help to increase the resilience of vehicle systems and decrease reliance on rigid and set driving rules [10], [11].

Significant progress has been made in autonomous driving technology. Nevertheless, safety concerns remain a major challenge for large-scale deployment. Autonomous systems need to work reliably across diverse driving environments, and need to be designed to safely operate in edge cases. There is a great deal of unsolved research in ensuring autonomous decisions are safe, that systems operate reliably within given safety margins, validating decisions, and designing systems with guaranteed safety and reliability across multiple operating domains. In addition, performance of learning-based autonomous driving systems degrades for conditions outside the training conditions, making extensive simulation and real-world validation a necessity before deployment [16].

Agentic AI systems base their advanced reasoning and decision making on sophisticated neural networks and reinforcement learning, making these systems very challenging to interpret [11]. In safety-critical domains like autonomous driving, machines should be capable of explaining their decisions to engineers, regulators, and passengers in a way the decisions can be verified and the system validated. Improving transparency and explainability can support system validation, debugging, safety assurance, regulatory compliance, and public trust. Safe and trustworthy autonomous systems rely on explainable AI to support model inspection, auditing, and accountability [17].

Situations involving multiple objectives can occur with autonomous driving. An example includes prioritizing the balance of protecting the passengers, pedestrians, and adhering to traffic laws [2], [18]. Agentic A.I. presents ethical problems because agents are able to evaluate alternatives and choose actions with a minimum of human oversight [11]. Consequently, these issues of accountability, transparency, privacy, fairness, and public acceptance become the focus of ethical and legal research and design. These concerns can be addressed with a combination of appropriate governance mechanisms, legal responsibility frameworks, and regulations to support the safe and responsible deployment of autonomous driving systems [2], [10].

## 2.5 Hardware and Circuit-Level Enablers for Agentic AI in Autonomous Vehicles

The functional requirements of Agentic AI discussed in the previous sections cannot be separated from the computing hardware that executes perception, decision-making, and planning in real time. Computing hardware is an essential element of Agentic AI systems. Agentic AI systems rely on computationally intensive neural network inference, and computing hardware trade-offs such as latency, power consumption, and heat dictate the level of SAE automation that can realistically be supported. In this section, some common architectures of hardware capable of executing Agentic AI, challenges at the circuit level of multi-

sensor fusion, and some embedded computing products aligned to the SAE automation levels from Section 2.2, will be discussed.

### 2.5.1 Specialized Computing Architectures for Agentic AI Inference

Deep learning workloads in autonomous vehicles make use of Graphics Processing Units (GPUs) because their parallel architecture is well suited to perform the matrix operations used in convolutional and transformer neural networks. The drawback to using GPUs is that they use a lot of power, create a lot of heat, and introduce challenges due to thermal management, which must be addressed within a vehicle's cooling system and power budget [19].

Field Programmable Gate Arrays (FPGAs) can be used to perform some sensor data preprocessing or speed up certain layers in neural networks and bypass the processor, reducing end-to-end latency while using less energy than traditional methods [19]. Application-Specific Integrated Circuits (ASICs), similar to Tesla's Full Self-Driving Computer or the EyeQ family from Mobileye, integrate dedicated neural network accelerators and general-purpose cores within a single chip and achieve up to 7 times higher energy efficiency and up to a 93-fold reduction in tail latency compared to GPU-based solutions for object detection [20].

Spiking Neural Networks (SNNs) are an alternative approach that uses event-driven or asynchronous computation, which allows for further reduction in power consumption compared to frame-based processing and is ideal for size-, weight-, and power-constrained perception systems in vehicles. However, limited deployment at the automotive scale is caused by fragmented integration between hardware, training methods, and datasets [21].

### 2.5.2 Hardware Implementation of Multi-Sensor Fusion

The Agentic AI capabilities described in Section 2.3, particularly environmental interaction and adaptive decision making, depend on the real-time fusion of high-bandwidth data streams from cameras, radar, and LiDAR. Autonomous driving platforms must process these multi-modal sensor streams at frame rates of approximately 10 to 30 Hz while completing detection, tracking, and planning within a few hundred milliseconds, which imposes severe constraints on both algorithm design and the underlying hardware.

Transformer-based fusion architectures, although effective at aligning heterogeneous sensor modalities, incur quadratic computational complexity with respect to the number of input tokens, making them difficult to deploy on resource-constrained onboard computing units without dedicated hardware acceleration. The sparsity of LiDAR point clouds further complicates hardware design, since conventional GPUs are optimized for dense matrix operations rather than the irregular, sparse data structures generated by LiDAR sensors.

To reduce end-to-end latency, some architectures route raw sensor data through an FPGA directly to the GPU, bypassing the central processing unit and reducing the sensor-to-decision pipeline delay. Memory bandwidth represents an additional constraint on sensor fusion hardware: three-dimensional stacked memory technologies, such as High-Bandwidth Memory, can provide on the order of 1 terabyte per second of bandwidth, roughly thirty times that of conventional GDDR5 memory, which is increasingly necessary to sustain the data movement required by deep multi-sensor fusion networks [19].

### 2.5.3 Power-Efficient Edge Computing Platforms and SAE-Level Compute Budgets

Commercially available embedded computing platforms illustrate how compute performance and power consumption scale with the targeted SAE automation level. The NVIDIA DRIVE Orin System-on-Chip delivers approximately 254 trillion operations per second (TOPS) of AI performance within a power budget of approximately 200 W and is positioned by its manufacturer to scale from Level 2+ driver assistance to full automation depending on the number of Orin units deployed in a given vehicle. Its successor, the NVIDIA DRIVE Thor System-on-Chip, delivers up to 1,000 INT8 TOPS per chip and is intended for redundant, dual-chip configurations supporting Level 4 automation [22].

Tesla's Full Self-Driving computer integrates a dedicated neural network accelerator delivering approximately 72 TOPS within a power budget below 40 W, while Mobileye's EyeQ6 High processor delivers approximately 34 TOPS at approximately 33 W for driver-assistance and partial-automation functions. Qualcomm's Snapdragon Ride platform is explicitly designed to scale across the SAE automation range, from approximately 10 to 30 TOPS within a sub-5 W power budget for windshield-mounted camera-based driver-assistance systems, up to more than 700 TOPS within approximately 130 W for Level 4 and Level 5 automated driving [23].

Table 2 summarizes representative embedded computing platforms and their approximate compute and power budgets across the SAE automation

levels discussed in Section 2.2, illustrating the increasing hardware demands associated with the transition from driver assistance to full automation described throughout this paper.

Table 2. Representative embedded computing platforms and approximate compute and power budgets across SAE automation levels

| SAE Level(s) | Representative Platform | Approx. Compute Budget | Approx. Power Budget |
|---|---|---|---|
| Level 0-1 | Mobileye EyeQ6 High / entry Snapdragon Ride SoC | ~10-34 TOPS | ~5-33 W |
| Level 2 | NVIDIA Jetson AGX Orin | ~200 TOPS | ~40-60 W |
| Level 3 | NVIDIA DRIVE Orin | ~254 TOPS | ~200 W |
| Level 4 | Dual NVIDIA DRIVE Orin / high-end Snapdragon Ride | ~500-700+ TOPS | ~130-200 W |
| Level 5 | Dual NVIDIA DRIVE Thor (Hyperion) | >1,000 TOPS per chip | ~350 W per chip |

*Source: created by the authors*

As shown in Table 2, the transition from SAE Levels 0-1 to Levels 4-5 corresponds to roughly a twenty-to-thirty-fold increase in AI compute throughput and a substantial increase in power consumption, broadly consistent with the increasing Agentic AI requirement summarized in Table 3 [19], [22], [23]. This correspondence between the conceptual Agentic AI requirement and the physical compute and power budgets of representative automotive hardware provides a circuit-level counterpart to the functional analysis presented in Section 4.

# 3 CARLA-Based Illustrative Scenarios

## 3.1 CARLA Simulator Overview

CARLA (Car Learning to Act) is an open-source platform that makes it easier to develop, train, and validate autonomous driving systems. In 2017, CARLA was created to help research autonomous driving in realistic urban environments with configurable traffic scenarios and freely available digital assets for experimentation. Because CARLA was designed to aid the development of systems that perceive, plan, and control an autonomous vehicle, it can be used in all stages of development, from training and validation to simulation [13], [24].

The simulator is built on Unreal Engine 4 (UE4), which provides high-quality graphics rendering and realistic physics simulation. CARLA follows a client–server architecture in which the simulation environment is executed on the server while autonomous driving algorithms interact with the simulator through a Python client. This architecture separates the simulation environment from the autonomous driving software, allowing independent development of client applications while enabling efficient communication between the client and the simulator [13].

CARLA's flexibility is a major benefit. Researchers are able to develop and set environmental context using weather, lighting, traffic, pedestrian, and vehicle conditions and configurations of sensors. CARLA supports multiple forms of sensors, including RGB and ground-truth depth and semantic segmentation. It provides detailed ground-truth for perception and control algorithm evaluation. These make CARLA particularly suitable for performing research and validating autonomous systems in different traffic conditions and environments that are potentially hazardous and difficult or unsafe to reproduce in the real world [13].

Invoking simulation to inform and support research of autonomous driving has become standard practice. The reason is that simulation allows for evaluation of autonomous driving algorithms in a safe, cost-effective manner, and in a timely manner. Of the available simulators, CARLA is one of the most widely adopted open-source simulators because of its realism, flexibility, and community support [4].

New studies show that CARLA has been used in several research fields like perception, localization, motion planning, sensor fusion, reinforcement learning, validation, and assessment of driving safety. As CARLA is compatible with major autonomous driving software stacks like Autoware and Apollo, it offers even greater usefulness in developing and assessing driving systems in realistic simulation environments [4].

CARLA is now also commonly used to test different types of autonomous agents in customized traffic conditions. Frameworks such as PCLA extend CARLA by providing a seamless framework to deploy and assess several pre-trained agents in customized environments and traffic scenarios without relying on the original CARLA Leaderboard codebase. As a result, researchers are able to test various autonomous driving agents

under identical experimental conditions and are also able to construct and evaluate custom environments, thereby fostering controlled environments and standardized assessment [15].

The ability of CARLA to produce complex urban situations with plenty of cars, pedestrians, variable weather, and dynamic environmental interactions is an advantage. Researchers can use such a system to examine the driving behaviors of different agents in situations that would be difficult, expensive, or unsafe to create on public roads, while maintaining full experimental control [14].

Altogether, CARLA's features support the development and evaluation of autonomous driving systems.

The simulator incorporates multiple urban maps containing realistic design and layout of streets, intersections, traffic signs, traffic lights, lane markings, sidewalks, as well as the surrounding physical infrastructure. These environments allow a researcher to place an autonomous vehicle into a variety of driving scenarios, from a single street segment to a complex urban intersection setting. Environmental conditions such as rain, fog, cloud cover, and different times of day can also be configured to increase scenario diversity.

CARLA allows for the simulation of vehicles and pedestrians based on specified traffic behaviors. Researchers can set the number and placement of surrounding vehicles while providing control over traffic flow patterns. Entities are set to behave according to traffic behaviors, such as lane following, obeying traffic lights, and navigating through intersections while interacting with the ego vehicle. This allows for a wide variety of situations to be created and tested with regard to the development of algorithms for autonomous driving systems [13].

CARLA has many diverse and complementary sensing capabilities. The offering includes support for a large variety of sensing systems, including: RGB camera, depth, and semantic segmentation cameras, LiDAR, radar, GNSS, IMU, collision and lane invasion sensors, as well as other sensors included in recent CARLA releases. These sensors generate realistic data streams, allowing perception, localization, and sensor fusion algorithms to be built and validated before real-world use [13], [14].

The main method for interacting with CARLA is the Python API. This API allows users to spawn vehicles, configure sensors, generate traffic, modify weather conditions, collect sensor data, and control the behavior of a vehicle programmatically. The API enables access to modifiable environmental parameters, objects and ground truth, which makes it suitable for building custom applications and autonomous driving simulations [13].

This combination of capabilities allows CARLA to be one of the most comprehensive and versatile open-source autonomous driving simulation platforms for research and education [4], [13].

### 3.2 Illustrative SAE Automation Scenarios

To illustrate the functional differences between the six SAE J3016 automation levels, representative driving scenarios and conceptual system architectures are presented in this section. Together, these examples illustrate the progressive transition from manual driving to full driving automation, highlighting the increasing responsibilities of the ADS and the corresponding reduction in human driver involvement across the different SAE automation levels.

In SAE Level 0 (No Driving Automation), the human driver performs the entire dynamic driving task. All steering, acceleration, braking, and monitoring of the driving environment remain the responsibility of the human driver, while the vehicle may only provide warning or momentary intervention systems without sustained driving automation.

Figure 1 illustrates a manual driving scenario implemented in CARLA, where the ego vehicle is operated entirely by the human driver. No automated system performs sustained longitudinal or lateral vehicle control, making the scenario representative of SAE Level 0 driving.



Fig. 1: SAE Level 0 simulation in CARLA – manual driving
*Source: created by the authors*

Level 0 Scenario Functional Architecture is shown in Figure 2. For driver inputs, the system includes steering, acceleration, and braking. The driver is responsible for monitoring the driving environment and deciding on all aspects of the driving procedure. The system executes the commands of the driver. The system does not perform any type of sustained automation.

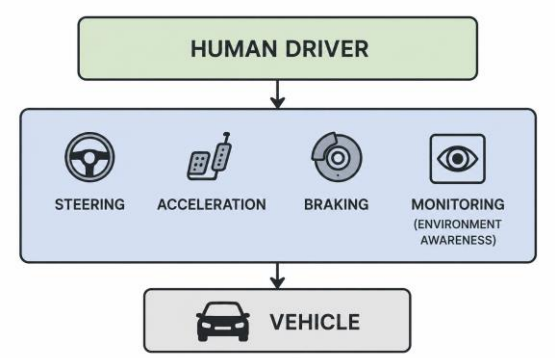


Fig. 2: Conceptual functional architecture of an SAE Level 0 driving system.
*Source: created by the authors*

In SAE Level 1 (Driver Assistance), the vehicle is capable of assisting the driver with either longitudinal or lateral vehicle control, but not both simultaneously. In the illustrative architecture presented in this study, the automation function is represented by Cruise Control, which performs longitudinal control by maintaining the desired vehicle speed through automatic acceleration and braking. However, the human driver remains responsible for steering, monitoring the driving environment, and performing all remaining aspects of the dynamic driving task in accordance with the SAE J3016 definition [5].

Figure 3 illustrates the functional architecture of an SAE Level 1 driver assistance system. The driver retains full responsibility for lateral vehicle control and environmental monitoring, while the Cruise Control system assists only with longitudinal control. Automated speed control systems allow automatic speed control, but the system can't steer and makes no driving decisions. Therefore, the driver must remain attentive and be ready to take control at all times.

In SAE Level 2 (Partial Driving Automation), the driving automation system is capable of simultaneously performing both lateral and longitudinal vehicle control while the human driver remains responsible for supervising the driving environment. In the illustrative scenario presented in this study, these functions are implemented using the CARLA Autopilot, which automatically controls steering, acceleration, and braking. According to the SAE J3016 definition, the driver should monitor the surroundings at all times, and should be ready to take control at a moment's notice [5].

Figure 4 shows a Level 2 driving situation made in CARLA. In this situation, autopilot is enabled. The driving automation system can control the lateral position and vehicle speed of the ego vehicle without continuous driver input. Although the system performs both lateral and longitudinal vehicle control under normal operating conditions, the human driver remains responsible to supervise the driving environment and be ready to resume manual control whenever necessary.

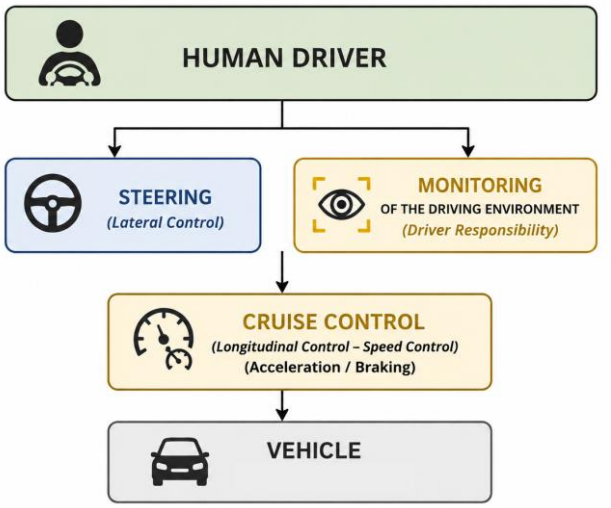


Fig. 3: Conceptual functional architecture of an SAE Level 1 driver assistance system.
*Source: created by the authors*




Fig. 4: SAE Level 2 (Partial Driving Automation) simulation in CARLA with autopilot enabled.
*Source: created by the authors*

Figure 5 illustrates the functional architecture of the implemented Level 2 system. Environmental information is acquired through onboard sensors and processed by the perception module before being used by the driving automation system. The driving automation system integrates Lane Keeping Assist and Adaptive Cruise Control to provide simultaneous lateral and longitudinal vehicle control. Despite this automation, monitoring of the driving environment remains the responsibility of the human driver, who can override the system through manual intervention whenever necessary.

In SAE Level 3 (Conditional Driving Automation), the ADS performs the complete Dynamic Driving Task (DDT) within its ODD. The ADS is responsible for both lateral and longitudinal

vehicle control, as well as monitoring the driving environment while operating within its intended conditions. However, if the ADS determines that it can no longer perform the Dynamic Driving Task safely within its ODD, it issues a Takeover Request, requiring the human driver to resume control of the vehicle [5].

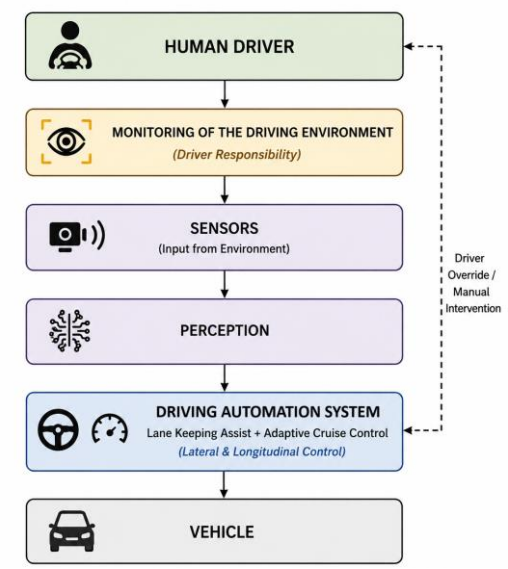


Fig. 5: Conceptual functional architecture of an SAE Level 2 (Partial Driving Automation) system.
*Source: created by the authors*

Figure 6 illustrates an illustrative SAE Level 3 driving scenario developed in the CARLA simulator. If operating normally, an ego vehicle should act independently within the given simulation scenario. An example of such a scenario is when a road obstruction is detected. This case generates a Takeover Request that shows the response of a Level 3 SAE system that instructs the driver to take back control of the vehicle after the Automated Driving System (ADS) can no longer safely handle the Dynamic Driving Task within its ODD.

Figure 7 presents the subsequent stage of the scenario, in which the human driver successfully resumes control following the takeover request. This transition illustrates one of the defining characteristics of SAE Level 3 automation, where the ADS performs the Dynamic Driving Task under normal operating conditions but transfers control to the human driver whenever it is no longer able to operate safely within its ODD.

Figure 8 illustrates the general functional architecture of an SAE Level 3 (Conditional Driving Automation) system. Environmental information acquired from onboard sensors is processed by the perception module before being supplied to the ADS, which performs decision making, motion planning, and vehicle control.




Fig. 6: SAE Level 3 (Conditional Driving Automation) simulation in CARLA showing a takeover request after detecting a road obstruction.
*Source: created by the authors*




Fig. 7: Human driver takeover following the takeover request in the SAE Level 3 driving scenario.
*Source: created by the authors*

The Driver Monitoring System (DMS) monitors the driver's ability to intervene. The Automated Driving System (ADS) issues a Takeover Request when it determines it can no longer carry out the Dynamic Driving Task within its Operational Design Domain (ODD). The DMS helps assess the driver's ability to take over and carry out the driving task in a safe manner and facilitates the transfer of control from automated to manual driving.

In SAE Level 4 (High Driving Automation), the ADS performs the complete DDT and monitors the driving environment within its ODD. Unlike SAE Level 3, the ADS is capable of autonomously handling driving situations that occur within its ODD without requiring immediate intervention from the human driver. If a situation remains within the defined ODD, the ADS continues operating autonomously without issuing a Takeover Request. If the ADS is unable to continue operating within its ODD, it is capable of achieving a minimal risk condition without relying on driver intervention [5].

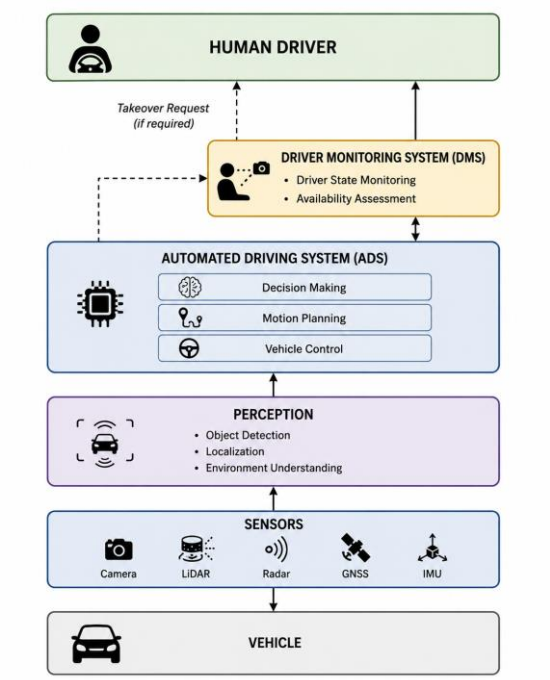


Fig. 8: Conceptual functional architecture of an SAE Level 3 (Conditional Driving Automation) system.
*Source: created by the authors*

Figure 9 shows an SAE Level 4 driving case made for the CARLA simulator. This case shows autonomous obstacle avoidance in the Operational Design Domain (ODD). As the ego vehicle approaches a road obstruction, the obstacle avoidance logic of the autonomous driving system detects the obstruction, plans a new trajectory, and performs an autonomous lane change maneuver. Once the vehicle passes the obstruction, the lane change is completed and the vehicle is back on its original trajectory and continues driving without requiring manual intervention.

The architecture of an SAE Level 4 high automation system is depicted in Figure 10. Multiple onboard sensors provide the system with environmental data. This data is processed by the perception module in order to generate an understanding of the environment. The Situation Assessment module evaluates the driving situation and detects driving hazards and suggests suitable driving maneuvers. Based on the above information, the ADS performs both decisions and plans movements to create an avoidance trajectory or an alternative route when necessary. The vehicle control module executes the control commands, and the automation system operates the vehicle within its Operational Design Domain (ODD) without the need for a Takeover Request as in SAE Level 3. The ADS is equipped to manage the complete Dynamic Driving Task to the extent of achieving a minimal risk condition in case it cannot operate within its ODD.




Fig. 9: Illustrative SAE Level 4 (High Driving Automation) scenario in CARLA: (a) the ego vehicle approaches a road obstruction; (b) the autonomous driving logic detects the obstacle and initiates autonomous lane avoidance; (c) the vehicle successfully avoids the obstruction and continues driving without issuing a takeover request.
*Source: created by the authors*

SAE Level 5 (Full Driving Automation) represents the highest level of vehicle automation defined by the SAE J3016 standard. At this level, the ADS performs the complete DDT under all roadway and environmental conditions that can be managed by a human driver. Unlike the lower automation levels, Level 5 does not require a human driver to supervise the driving task or to intervene during vehicle operation. Consequently, no Takeover Request is generated, as the ADS is expected to perform the entire driving task independently.

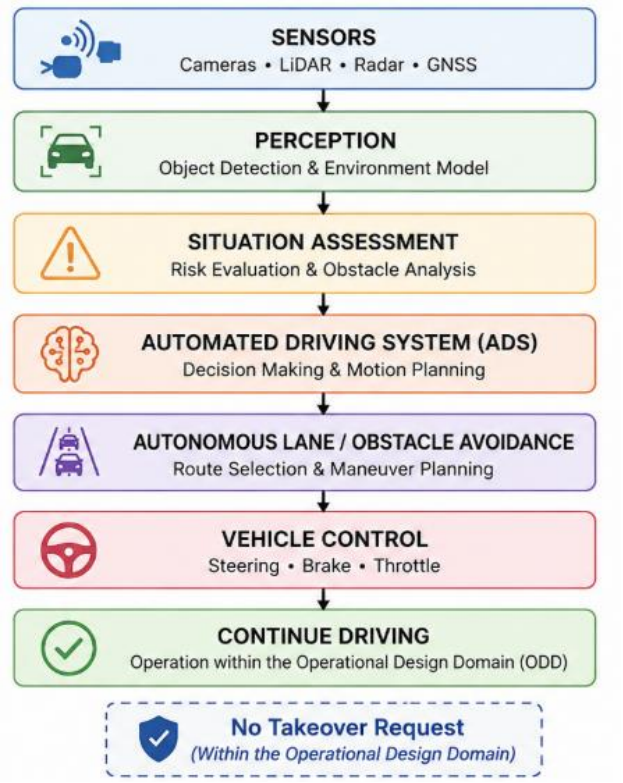


Fig. 10: Conceptual functional architecture of an SAE Level 4 high automation system.
*Source: created by the authors*

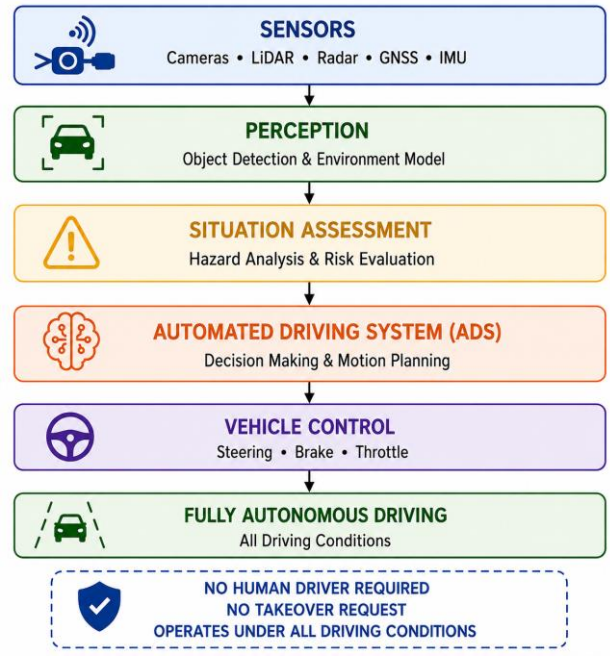


Fig. 11: Conceptual functional architecture of an SAE Level 5 full driving automation system.
*Source: created by the authors*

Figure 11 shows the main functional architecture for an SAE Level 5 full driving automation system. Multiple onboard sensors collect environmental data which is processed by the perception module to create an environment representation. The Situation Assessment module evaluates road conditions, traffic participants, and hazards, while the ADS makes decisions, plans motion, and generates trajectories, and subsequently generates control commands to the vehicle control module. When coupled, these units allow the automated driving system to do the complete Dynamic Driving Task autonomously. This is achieved under all roadway and environmental conditions that a human driver is capable of managing, and in the absence of human supervision or intervention.

# 4 Discussion

## 4.1 Comparison of SAE Automation Levels from an Agentic AI Perspective

The SAE J3016 standard defines six levels of automation in vehicles based on how the human driver and the ADS split responsibilities. As the level of automation rises, progressively greater responsibility for each element of automation (perception, decision making, planning, and execution) is assumed by the ADS, while the driver's duties are reduced.

From the Agentic AI lens, with automation, one can expect an increase in decision-making complexity and the system's autonomy. Traditional automation can take care of lower SAE levels, where the driver is expected to supervise the driving task. In the higher levels, the ADS must be capable of reasoning in context, planning, and adaptively coping with unpredictable environments, and deciding based on goals. These traits are considered the hallmarks of Agentic AI [10], [11].

Decision-making complexity, the level of automation and involvement of human users are noted in Table 3. Also, the requirement for Agentic AI capabilities is indicated. Table 3 presents the authors' conceptual interpretation of the relationship between SAE automation levels and the increasing relevance of Agentic AI capabilities.

Table 3 describes the evolution of automation levels and the accompanying changes in the role and focus of the driver. As the name suggests, Level 0 involves no automation. At Level 2, some driving functions are automated, but the ADSs are limited to specific algorithms and the driver is expected to continuously supervise the system and remain responsible for monitoring the driving environment and safety critical decisions. Therefore, the implementation of Level 2 does not require sophisticated Agentic AI technologies [5], [11].

Table 3. Comparison of SAE automation levels from an Agentic AI perspective.

| SAE Level | Human Role | Decision Complexity | Agentic AI Requirement |
|---|---|---|---|
| Level 0 – No Driving Automation | Full | Low | None |
| Level 1 – Driver Assistance | Full | Low | None |
| Level 2 – Partial Driving Automation | High | Low | Low |
| Level 3 – Conditional Driving Automation | Moderate | Medium | Moderate |
| Level 4 – High Driving Automation | Minimal | High | High |
| Level 5 – Full Driving Automation | None | Very High | Very High |

*Source: created by the authors*

Implementation of Level 3 ADS technology shifts the driving supervision responsibility to the ADS, which then performs the complete Dynamic Driving Task within the Operational Design Domain (ODD). The ADS is required to determine if it is safe to continue operating. The ADS is now required to make decisions that are context sensitive and decide when to generate a Takeover Request. As described in [5], [10], [11], this type of context sensitive, goal directed, and autonomous decision making shares several characteristics of Agentic AI.

SAE Levels 4 and 5 define higher levels of autonomous operation, where the ADS must be able to perceive the driving environment, perform risk assessment and generate alternative driving strategies to achieve safe goals, and continuously adapt its behavior to changing traffic conditions. This definition describes Agentic AI in terms of autonomy, goal directed behavior, environmental interaction, continuous adaptation, and long-term decision making.

The comparison shows that Agentic AI becomes increasingly important at more advanced levels of SAE automation. For lower SAE levels, traditional automation techniques are still appropriate. For more advanced levels of automation, intelligent systems that can reason for themselves, make plans, and make autonomous and adaptive decisions in unpredictable and changing environments will be required. The characteristics of Agentic AI align best with these advanced automation levels, particularly SAE Levels 4 and 5 [10], [11].

### 4.2 Where Does Agentic AI Become Necessary?

Along with the shift from manual driving to full autonomy, the duties of the Automated Driving System (ADS) expand continually. The SAE automation level determines the portion of the driving duty the ADS is assigned. This leads to a gradual decrease in the burden on the driver [5].

Lower level SAE automation applications make extensive use of control algorithms and human oversight. Higher SAE automation levels impose greater burdens on the ADS in the areas of perception, evaluation, decision-making and execution, and behavioral adaptation, all of which occur under changing traffic conditions. These types of capabilities are typical of Agentic AI, meaning that as the demand for higher order SAE automation grows, capabilities associated with Agentic AI become more important [10], [11].

The human driver continues to be responsible for supervising the driving environment and retains control for all major driving decisions at SAE Levels 0, 1 and 2. Cruise Control, Adaptive Cruise Control and Lane Keeping Assistance systems operate by control algorithms and do not select driving objectives or perform long-term planning.

From the Agentic AI perspective, automation levels of SAE Levels 0 to 2 typically do not require autonomous reasoning or goal-directed planning. Most driving assistance functions are generally implemented with conventional control systems, rule-based algorithms, or task-specific AI systems as responses to defined sensor inputs. Since the human driver oversees the driving situation and is accountable for making safety-related decisions, ADS does not have to analyze complicated situations and undertake long-term autonomous planning. Thus, the abilities usually related to Agentic AI are generally not required to fulfill the operational requirements of SAE Levels 0 to 2, since the systems perform only a few driving assistance functions while the human driver is required to maintain responsibility for supervision of the driving situation and the DDT [5], [10], [11].

SAE Level 3 is the first automation level where the ADS is required to monitor the driving situation and perform the entire DDT within its ODD. In this case, the ADS is required to make a greater number of operational decisions, since the ADS must assess, on an ongoing basis, if it is safe to continue functioning, or if a Takeover Request is required.

Unlike Levels 0-2, Level 3 demands ADS interpretation of dynamic traffic scenarios to recognize operational limits and make context-dependent decisions in uncertain environments. Such activities have several traits of Agentic AI consisting of context-awareness and adaptability within the predetermined boundaries of operational constraints for autonomous decision making.

For most Level 3 cases, existing automation technologies continue to be applicable. However, the Agentic AI traits become increasingly relevant with the additional emphasis on contextual thinking, situational analysis, and flexibility in decision making. Indeed, the use of Agentic AI is likely to assist the ADS in augmenting contextual reasoning, situational analysis, and flexibility in decision making as the ADS approaches the operational constraints of its ODD [10], [11].

Agentic AI becomes considerably more significant at SAE Level 4. At this level, the ADS is required to perform complete DDT within its operational design domain (ODD) and continually monitor the driving environment. This is accomplished without the need for immediate human intervention [5]. The ADS is expected to understand the contextual driving situation and identify potential threats in the driving environment and adopt a variety of different driving strategies in order to perform safe maneuvers and maintain a continuous driving operation.

These functional requirements overlap with Agentic AI in many respects. The ADS has to be able to understand the makeup of a situation and the possible implications of different actions. It is also required to be able to formulate safe driving trajectories and to alter its behavior based on the situation and the presence of uncertainty and change. These behaviors include autonomous planning, continued interaction with the environment, goal-oriented behavior, and adaptive decision-making. Agentic AI systems, typically, exhibit these features and behaviors. The scenario outlined in this study showcases the process. The ADS does not require the driver to intervene when it encounters an obstruction on the road. It evaluates the obstruction, chooses a new trajectory, performs a lane change, and continues to engage in safe driving behavior, all within the bounds of the Operational Design Domain (ODD).

SAE Level 5 describes the greatest level of vehicle automation, where the ADS has the ability to execute all functions in the DDT as a substitute for the human driver under all roadway and environmental conditions that a human driver is able to address. Unlike all the other levels of automation, no supervision or intervention by a human driver is required when the vehicle is in motion.

The system must perceive and respond to a changing environment, reason under uncertainty, make decisions, perform long-horizon planning, and continuously alter its behavior to meet the requirements of several circumstances. Driving decisions must be made independently to ensure safe operation and conformity to traffic regulations.

From this viewpoint, the characteristics of Agentic AI are similar to the capabilities of SAE Level 5 automated driving systems. Autonomous reasoning, goal-oriented behavior, long-horizon planning, environmental interaction, and adaptive decision making provide a conceptual framework for full driving automation described in the literature.

It must be stated that while this study attempts to analyze the relationship between SAE automation levels and the part that Agentic AI may play, some limitations must be recognized.

The first of these is the predominantly conceptual and analytical nature of the work. The discussion is grounded in the SAE J3016 standard, the literature on Agentic AI, and some exemplar driving scenes developed in the CARLA simulator. Therefore, the findings in this study must be regarded as an analytical comparison rather than as empirical results validated by an experiment.

Second, CARLA simulations illustrate the functional characteristics of the SAE automation levels rather than evaluate a complete autonomous driving system. The simulations include example scenarios with behaviors such as autonomous lane-keeping, obstacle avoidance, and takeover requests, but are not meant to be a comprehensive validation of the autonomous driving algorithms under a wide range of real-world traffic conditions.

Third, no quantitative analysis was performed on Agentic AI to evaluate its effect on the performance of autonomous driving. In this case, metrics such as the accuracy of decisions, the quality of trajectories, the efficiency of the system, the robustness of the system, and improvements of safety were not evaluated, and, thus, the focus is on the conceptual relationship between the SAE level automation functions and Agentic AI.

Finally, the comparison made in this chapter is defined on the basis of the latest scientific publications on Agentic AI. Agentic AI remains an active and rapidly evolving research area. Future advances in this field could well define the relationship with autonomous driving systems in a better way.

### 4.3 Circuit- and Hardware-Level Perspective on the Agentic AI Requirement

The items in Table 3 that describe functional aspects of Agentic AI are related to the compute and power budgets of the embedded platforms discussed in Section 2.5. The low Agentic AI requirement for SAE Levels 0-2 is related to camera-centric System-on-Chip solutions containing a few tens of TOPS and operating within a few watts to a few tens of watts, with a particular set of control algorithms and limited onboard reasoning [19], [23].

The Level 3 Agentic AI requirement corresponds to platforms in the range of about 200 to 250 TOPS and 40 to 200 W, as more computing power is required to monitor the driving environment and determine whether a Takeover Request should be issued. Level 4 and 5 Agentic AI requirements correspond to platforms delivering several hundred to more than a thousand TOPS of compute power, with power budgets from approximately 130 W to several hundred watts, often in multi-chip or redundant multi-chip setups to satisfy automotive functional safety requirements [22], [23].

From this, it can be inferred that the Agentic AI requirement introduced in this work is more than just a qualitative requirement. It reflects the compute per watt trends in commercially available automobile technology. Thus, specialized hardware architectures and circuits are relevant to the realization of Agentic AI capabilities in future autonomous driving systems.

## 5 Conclusion

This study analyzes the association of SAE Levels of Driving Automation and Agentic AI. We conducted a literature review and conceptual analysis with case example driving scenarios and general functional architectures to examine the shift of the responsibilities and associated capabilities of the ADS with progressing levels of vehicle automation.

We found a developing demand for environmental perception and decision making combined with adaptive planning as automation progresses through levels and ultimately reaches full automation. Driving functions at lower SAE levels of automation require ADS to perform with considerable levels of human supervision, while higher automation levels and functions require ADS to operate with greater autonomy.

The higher we go with the levels of vehicle automation, the more relevant Agentic AI capabilities will become. With higher levels, the emphasis will be on reasoning, goal orientation, environmental interaction, adaptive decision making and long-horizon planning. Our analysis utilizes a purely conceptual approach and thus neither builds nor evaluates Agentic AI systems. However, it does represent a structured comparison of Agentic AI and the ways in which it relates to the development of future autonomous driving systems.

This paper offers examples of driving scenarios and associated functionality and architecture at different SAE automation levels, which help to illustrate the automation levels and to better compare driving automation to Agentic AI. They also help to discern what function the ADS performs at the varied levels of automation.

Beyond the conceptual comparison, our review of specialized computing architectures, multi-sensor fusion hardware, and representative embedded automotive platforms shows an increase in Agentic AI requirements across SAE automation levels corresponds to an increase in the compute throughput and power budgets of commercially available SoCs. This adds a circuit-level grounding to the conceptual framework in this paper.

Future work can focus on how and where Agentic AI can fit into the framework of autonomous driving and assess its impacts on the systems of perception, planning, decision making, and actual driving behavior in driving simulations and in the real world. This may provide further insight on Agentic AI and the potential that it holds for future iterations of autonomous driving.

*Acknowledgement:*
The authors acknowledge the use of large language model assistants for language refinement, editorial review, and consistency verification during the preparation of this manuscript. All literature selection, conceptual development, simulation scenarios, analysis, interpretations, and conclusions are the authors' own. The authors carefully reviewed and edited all AI-generated content and take full responsibility for the accuracy and integrity of this publication.

**Declaration of Generative AI and AI-assisted Technologies in the Writing Process**

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The

author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

*References:*

[1] F. B. Scurt, T. Vesselenyi, R. C. Tarca, H. Beles, G. Dragomir, Autonomous Vehicles: Classification, Technology and Evolution, *IOP Conference Series: Materials Science and Engineering*, vol. 1169, no. 1, Art. no. 012032, Aug. 2021, doi:10.1088/1757-899X/1169/1/012032.

[2] International Transport Forum (OECD), *Automated and Autonomous Driving: Regulation under Uncertainty*, Corporate Partnership Board Report, 2015.

[3] N. Souweidane, B. Smith, *State of ADAS, Automation, and Connectivity*, Center for Automotive Research, 2023.

[4] N. Aliane, A Survey of Open-Source Autonomous Driving Systems and Their Impact on Research, *Information*, vol. 16, no. 4, Art. no. 317, 2025, doi:10.3390/info16040317.

[5] SAE International, *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles (SAE Standard J3016_202104)*, Warrendale, PA, USA, Apr. 2021.

[6] D. Hopkins, T. Schwanen, Talking about automated vehicles: What do levels of automation do?, *Technology in Society*, vol. 64, 2021.

[7] E. Stayton, J. Stilgoe, It's Time to Rethink Levels of Automation for Self-Driving Vehicles, *IEEE Technology and Society Magazine*, vol. 39, no. 3, pp. 13–19, 2020.

[8] E. R. Teoh, What's in a name? Drivers' perceptions of the use of five SAE Level 2 driving automation systems, *Journal of Safety Research*, vol. 72, pp. 145–151, 2020.

[9] T. Inagaki, T. B. Sheridan, A critique of the SAE conditional driving automation definition, and analyses of options for improvement, *Cognition, Technology & Work*, vol. 21, pp. 569–578, 2019.

[10] S. Hosseini, H. Seilani, The Role of Agentic AI in Shaping a Smart Future: A Systematic Review, *Array*, vol. 26, Art. no. 100399, 2025, doi:10.1016/j.array.2025.100399.

[11] D. B. Acharya, K. Kuppan, B. Divya, Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey, *IEEE Access*, vol. 13, pp. 18912-18936, 2025, doi: 10.1109/ACCESS.2025.3532853.

[12] J. Schneider, Generative to Agentic AI: Survey, Conceptualization, and Challenges, *arXiv preprint arXiv:2504.18875*, 2025, doi:10.48550/arXiv.2504.18875.

[13] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, V. Koltun, CARLA: An Open Urban Driving Simulator, *arXiv preprint arXiv:1711.03938*, 2017, doi:10.48550/arXiv.1711.03938.

[14] D. Gorza, G. Saly, D. Csikor, Simulation of Environment Recognition Systems for Autonomous Vehicles in CARLA Simulator, *Engineering Proceedings*, vol. 113, Art. no. 30, 2025, doi:10.3390/engproc2025113030.

[15] M. J. Tehrani, J. Kim, P. Tonella, PCLA: A Framework for Testing Autonomous Agents in the CARLA Simulator, *arXiv preprint arXiv:2503.09385*, 2025, doi:10.48550/arXiv.2503.09385.

[16] P. Czechowski, B. Kawa, M. Sakhai, M. Wielgosz, Deep Reinforcement and Imitation Learning for Autonomous Driving: A Review in the CARLA Simulation Environment, *Applied Sciences*, vol. 15, no. 16, Art. no. 8972, 2025, doi:10.3390/app15168972.

[17] A. Kuznietsov, B. Gyevnar, C. Wang, S. Peters S. V. Albrecht, Explainable AI for Safe and Trustworthy Autonomous Driving: A Systematic Review, *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 12, pp. 19342-19364, Dec. 2024, doi: 10.1109/TITS.2024.3474469.

[18] C. Rus, M. Leba, A. Ionica, Road traffic control in the context of an environmental friendly smart city, *17th International Technical-Scientific Conference on Modern Technologies for the 3rd Millennium*, Oradea, ROMANIA, MAR 22-23, MODERN TECHNOLOGIES FOR THE 3RD MILLENNIUM, Page351-356, 2018.

[19] X. Wang, M. A. Maleki, M. W. Azhar, P. Trancoso, Moving Forward: A Review of Autonomous Driving Software and Hardware Systems, *arXiv preprint arXiv:2411.10291*, 2024, doi:10.48550/arXiv.2411.10291.

[20] R. Islayem, F. Alhosani, R. Hashem, A. Alzaabi, M. Meribout, Hardware Accelerators for Autonomous Cars: A Review, *arXiv preprint arXiv:2405.00062*, 2024, doi:10.48550/arXiv.2405.00062.

[21] M. Middleton, T. Ali, E. Baikas, B. Sen Bhattacharya, E. Vousden, M. A. Trefzer, Event-Based Vision at the Edge: A Review, *Brain Sciences*, vol. 16, no. 4, Art. no. 422, 2026, doi:10.3390/brainsci16040422.

[22] NVIDIA Corporation, NVIDIA DRIVE Hardware for Autonomous Vehicles, *NVIDIA online technical documentation*, 2025.

[23] Qualcomm Technologies, Inc., Qualcomm Snapdragon Ride Platform, *Qualcomm online technical documentation*, 2024.

[24] A. Berceanu, M. Leba, M. Risteiu, N. Mija, A. Ionica, Simulation of an Autonomous Car Drive Scenario, *2022 7th International Conference on Mathematics and Computers in Sciences and Industry (MCSI)*, Athens, Greece, 2022, pp. 170-174, doi: 10.1109/MCSI55933.2022.00034.

**Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)**

The authors contributed equally to all stages of the present research, from the formulation of the research problem to the analysis, conclusions, and preparation of the final manuscript.

**Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself**

No funding was received for conducting this study.

**Conflict of Interest**

The authors have no conflicts of interest to declare that are relevant to the content of this article.

**Creative Commons Attribution License 4.0 (Attribution 4.0 International, CC BY 4.0)**

This article is published under the terms of the Creative Commons Attribution License 4.0
https://creativecommons.org/licenses/by/4.0/deed.en_US