Methodologies to better handle the evolving requirements of autonomous vehicle perception systems

Master's Thesis in Computer science and engineering

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Abstract

The development of autonomous vehicles (AV) has become an emerging field with various advanced technologies like Machine Learning (ML) and Artificial Intelligence (AI). However, the dynamic nature of the automotive industry, with constantly evolving requirements, presents significant challenges in developing these perception systems. This study investigates the changing functional and non-functional requirements of AV perception systems, focusing on the challenges and consequences these systems face in adapting to environmental changes, technological advancements, and regulatory demands. Through qualitative interviews with professionals from leading automotive companies, including system designers, solution architects, and embedded software engineers, the research explores how different development methodologies, particularly agile approaches, are crucial in addressing these evolving requirements. The findings reveal that the functional requirements in AV perception systems are evolving toward AI-enabled perception, real-time data processing, and advanced sensor fusion to enhance object detection, localization, and environmental understanding. Non-functional requirements such as safety, cybersecurity, and system reliability are becoming more complex due to increasing expectations and regulatory pressures. These evolving needs lead to significant challenges, including sensor uncertainties, higher development costs, and decision-making difficulties, which are being addressed through adaptive software development practices like Agile, SAFe, and hybrid approaches that support flexibility and rapid iteration. The insights gained from this research aim to improve the development processes for AV perception systems development and provide important suggestions and insights for engineers and researchers in the AV perception system. This work sets the stage for future work to explore hybrid development methodologies, real-time data processing optimization, and the potential of cutting-edge technologies, such as quantum computing, to overcome current limitations in AV perception and decision-making processes.

Keywords: Autonomous vehicle, perception system, evolving requirements, sensor fusion, decision-making, agile methods, functional requirements, non-functional requirements, thematic analysis

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Soniya Abraham, Gothenburg, May 2025

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1

Introduction

The development of autonomous vehicles perception (AVP) systems has become one of the most transformative technological pursuits, promising safer roads, improved mobility, and increased traffic efficiency [8]. The development of AV perception systems is a rapidly advancing field that concentrates on high adaptability, precision, safety-critical systems, and real-time responsiveness. Perception systems [31] allow vehicles to understand and interact with their environment and it relies on a combination of real-time data processing, sensors, and machine learning algorithms that detect various elements such as road conditions, traffic signs, obstacles, and other vehicles. Perception system meets functional requirements that the perception system effectively detects, interprets and responds to the environment (e.g., accurate object detection[57], behavior prediction [6], and trajectory planning) while maintaining non-functional requirements such as safety, robustness [34], scalability, and real-time responsiveness [57].

However, designing perception systems for AVs (Autonomous Vehicles) presents unique challenges due to the constantly changing requirements of the real world[30]. For instance, perception systems must adapt to new scenarios, environmental variations, advancements in sensor technology, and regulatory standards. Perception systems in AVs face various challenges, including adverse weather conditions [27], sensor limitations, cybersecurity threats, and data integration issues. Babei et al., [6] and Parekh et al. [46] explore perception system architecture for self-driving vehicles, They describe different evolving functional and non-functional requirements, their challenges, and their effects. Traditional requirements engineering approaches often struggle to keep pace with these dynamic demands, as they are not designed to handle the continuous and unpredictable changes that characterize the AV development landscape. To address these challenges, various development methodologies offer a promising approach. For example: “agile methodologies” with their core principles of flexibility, iterative progress, and responsiveness to change are particularly valuable[29]. The thesis also explores how different development methodologies can help better manage the evolving requirements and frequent innovation in autonomous vehicle perception systems[9].

1.1 Problem statement

As per the studies of Gruyer [22] and Lobato [39], AVs cannot make safe driving decisions without accurate, dependable, and real-time data, which seriously puts at risk their ability to operate autonomously. According to Wang et al., [58] Despite developments in technology, fully autonomous vehicles are not yet ready for commercial deployment, primarily due to safety concerns arising from the constraints of the perception system such as sensor uncertainty, complexity of environmental conditions etc. Therefore, to achieve safe and reliable operation, evolving requirements must account for several key factors, including the complexity of real-world scenarios, changing stakeholder needs, rapid technological advancements [48], adverse weather conditions [6], and evolving fairness standards.

Overcoming challenges, such as complex environmental conditions [40], and sensor uncertainties, requires AVs to be equipped with robust and reliable perception systems[6]. According to the current state-of-the-art research, there is a need to conduct more empirical studies on the evolving requirements, challenges that arise, their effects, and various development methodologies [24][55][30]to address the requirements and challenges. Different development methodologies are considered, for example, agile [36], which fosters greater agility in responding to changing needs compared to traditional methods. An interview study design methodology is chosen to proceed with the research since it allows for in-depth and concrete knowledge exploration and understanding of evolving real-world scenarios like autonomous vehicles. This study focuses on solution architects, system designers, agile teams, and embedded software engineers operating in industrial contexts of autonomous vehicles (Zenseact, VOLVO, Univrsus, Polestar) using a qualitative research method.

1.2 Purpose of the study

Specifically, this study aims to identify the most evolving functional and non-functional requirements in autonomous vehicle perception (AVP) systems. It also examines common challenges that arise in AV or those that may cause the requirements to evolve, such as adverse weather conditions [27], sensor limitations, and uncertainties, along with challenges stemming from evolving needs, such as the complexity of risk assessment. The study analyzes the resulting impacts, including increased computational demands, software failures, and higher error rates [20]. Finally, the study explores how these challenges can be effectively addressed through current development practices and software engineering methodologies. In the case of the fast and evolving nature of AVP systems, development processes, such as agile or hybrid methods, demand continuous integration, flexibility, and rapid adaptation compared with traditional upfront requirements engineering (RE) [52]. According to Jebamikyous et al.,[31], automotive industries increasingly embed requirements management within iterative development activities rather than relying solely on static RE techniques. The fast progression of evolving requirements has resulted in the creation of progressively complex perception systems. However, these systems address significant challenges and consequences because of changing needs, including greater accuracy, compliance with safety regulations, real-time processing capabilities, etc. Due to limited research in this area [24][30], this study aims to identify the most evolving functional and non-functional requirements (such as innovative technology, fast decision-making, robustness, and safety), examine the key challenges and their impacts, and explore methodologies to manage these evolving needs effectively in autonomous vehicle perception systems. The research questions framed for this study are:

- **RQ1:** What are the most evolving functional requirements of autonomous vehicle perception systems development?

- **RQ2:** What are the most evolving non-functional requirements of the autonomous vehicle perception systems development?
- **RQ3:** What are the common challenges of autonomous vehicle perception systems development, and what challenges arise due to the evolving requirements in autonomous vehicle perception systems development?
- **RQ4:** What are the consequences of challenges in the autonomous vehicle perception system development?
- **RQ5:** How do we mitigate the consequences or challenges of the evolving requirements of autonomous vehicle perception systems development?

In this study, RQ1 and RQ2 focus on identifying the most evolving functional and non-functional requirements, such as real-time decision-making, accuracy, safety, and adaptability, which are essential in ensuring AVs can respond effectively to complex and unpredictable real-world scenarios. RQ3 examines the common challenges that AV perception systems face, including sensor limitations and adverse weather conditions, as well as the challenges that arise specifically to evolving requirements. while RQ4 explores the consequences of these challenges, such as increased computational demands and higher error rates. Finally, RQ5 seeks to identify different methodologies to address requirements and challenges, particularly through agile and hybrid, which offer flexibility and responsiveness to evolving requirements. The research questions systematically address the overall problem by identifying the evolving functional and non-functional requirements, uncovering associated challenges and consequences, and exploring adaptive development methodologies to ensure safe, reliable, and responsive autonomous vehicle perception systems.

1.3 Significance of the study

The significance of this study focuses on how different development methodologies can be customized to view the evolving requirements of AVP, its challenges, and consequences, ensuring real-time responsiveness and compliance with safety requirements. Perception systems perform a crucial role in the functioning and safety of AVs, as they enable vehicles to sense, interpret, and respond to the various functionalities and non-functionalities of the autonomous vehicle in real time. AV requirements' dynamic and unpredictable nature —spanning environmental changes, technological advancements, and regulatory demands poses significant challenges to traditional development methodologies. This study bridges this gap by examining the different evolving requirements of AV, identifying challenges and consequences arising from their evolving nature, and evaluating the efficiency of various development methodologies in tackling these issues.

This study could provide valuable insights to industrial practitioners, software engineers and developers, academic researchers, and multidisciplinary teams involved in AV development. This study's results may be utilized to adopt various software development methods in other safety-critical domains.

1.4 Thesis outline

The structure of this thesis is explained below: Section 2 describes the background. It provides an in-depth explanation of the significance of the study and establishes the context of the research. Section 3 describes Related work, provides knowledge about the existing research and studies on the topic, and recognizes gaps that motivate the current investigation. Section 4 describes the study design, the method, and other procedures. Section 5 describes the Result, which contains a detailed study of all the findings. Section 6 presents the Discussion regarding all the data obtained in the Result section, and finally, section 7 is about the conclusion of the thesis report.

2

Background

Autonomous vehicle perception system (AVP): Perception is the fundamental task of an autonomous vehicle's driving system [51]. Perception involves gathering information about the vehicle's surrounding environment. In simpler terms, perception systems act like the senses of an autonomous vehicle, allowing it to "see" and "understand" the world around it. Furthermore, perception systems involve sophisticated operations such as sensor fusion (merging data from multiple sources like LiDAR, radar, and cameras) and localization (determining the exact position of the vehicle on a map)[56]. Without a reliable perception system, an autonomous vehicle cannot navigate safely, since all planning and control decisions rely on an accurate understanding of the surroundings.

Requirements: Software requirements[37] define what a software system must do on behalf of its users or connected systems. Requirements in software engineering are typically classified into two major types: functional and non-functional requirements. Software requirements define what a software system must do on behalf of its users or connected systems. Some of the key functional requirements included in autonomous vehicles are object detection and recognition, scene recognition, human activity recognition, environment recognition, road signs detection, and so on [28]. These requirements enable the vehicles to perceive and interpret their environment precisely for safe navigation. Non-functional requirements define the "qualities" of a system rather than its specific behaviors. They address how well the system performs under various conditions. Some of the non-functional requirements are user acceptance, robustness, accuracy, and reliability.

Development methodologies Development processes refer to the structured methodologies that guide the planning, design, development, and testing of systems such as autonomous vehicle (AV) perception systems. These processes provide a systematic framework for managing the life cycle of a project and include models such as the Waterfall Model, agile Model, V-Model, and various hybrid approaches [32]. Each process defines specific workflows, activities, roles, and deliverables that ensure the development progresses in an organized and controlled manner [24]. In traditional industries, development processes often assume that system requirements remain stable over time. However, in dynamic fields like AV perception systems, where new technologies, environmental conditions, and regulations continuously evolve, traditional processes struggle to accommodate the necessary flexibility and responsiveness .

Agile methodology Agile is a flexible, iterative methodology that has been widely adopted to address the challenges associated with evolving requirements in complex system development [14]. It emphasizes collaboration between cross-functional teams, responsiveness to changing customer needs, and the frequent delivery of working software. In agile, individuals and interactions are valued more than rigid processes and tools, and it prioritizes [1]customer collaboration and adaptability over strict adherence to a fixed plan. In the development of AV perception systems, agile methodologies are particularly valuable as they accommodate rapid technological advancements, regulatory updates, and unforeseen environmental challenges.

Requirements engineering for perception system Requirements Engineering (RE) is a fundamental discipline within system and software development that focuses on the identification, documentation, analysis, validation, and management of system requirements [49]. In essence, RE defines what the system should do (functional requirements) and the qualities it must possess (non-functional requirements), such as safety, scalability, and real-time performance. It ensures that the developed system meets the needs of stakeholders, complies with regulatory standards, and operates effectively within its intended environment. In AV perception systems, RE plays a particularly critical role due to the need for precise, real-time, and reliable operation in highly dynamic and unpredictable environments [23]. Traditional RE practices, which rely on comprehensive upfront requirement specification, often fall short in contexts where requirements evolve frequently in response to technological, environmental, or stakeholder-driven changes. RE for the perception system is a complex and evolving field when it integrates with innovative technology such as ML.

Agile for RE: Agile Requirements Engineering as the "agile" way of planning, executing, and reasoning about RE activities [29], highlighting that agile methods are characterized by extensive collaboration, face-to-face communication, and self-organizing teams. It integrates agile principles into the traditional practices of Requirements Engineering (RE) to better manage evolving and uncertain requirements in AVP. Rather than attempting to define all system requirements comprehensively at the outset, agile RE emphasizes continuous elicitation, refinement, and prioritization of requirements throughout the development life cycle. This approach enables development teams to respond swiftly to changing needs, incorporate emerging technologies, and meet evolving regulatory standards effectively. In the context of autonomous vehicle (AV) perception systems, agile RE is particularly advantageous as it supports the flexibility and rapid adaptation necessary to address challenges such as sensor innovation, environmental variability, and complex safety requirements [25]. Agile RE fosters a development environment that is resilient, customer-focused, and better aligned with the realities of fast-paced technological evolution.

3

Related Work

This section presents a review of the existing research relevant to the study. It analyses the highly evolving functional and non-functional requirements of perception systems in AV, the challenges that arise from these requirements, and the effects or consequences of these challenges. Finally, it introduces the need and a solution to solve this problem effectively. Leffingwell [37] says that "functional requirements are usually action-oriented (when the user does x, the system will do y)".

3.1 Functional requirements of autonomous vehicle perception system

The development of perception systems has advanced due to the integration of advanced sensing technologies, machine learning algorithms, and real-time data processing and perception capabilities. The perception system must operate with real-time processing capabilities to respond to rapidly changing environments [30]. The figure 3.1 shows the functional requirements.

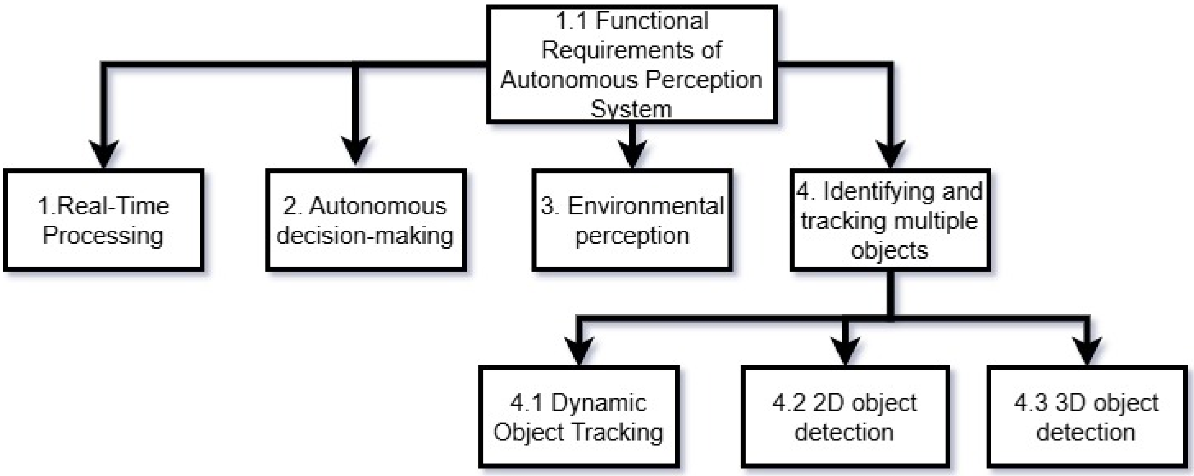

Figure 3.1: Functional requirements in AV perception system

Real-time processing: According to Babaei et al. [6], real-time processing capabilities help to make timely decisions and respond to rapidly changing situations. This requirement is essential for the vehicle to react promptly to dynamic conditions on the road.

Liu et al.[38] state the importance of minimizing latency in the perception system. For instance, they calculate that when an autonomous vehicle is moving at 40 km/h in an urban area and requires control updates every meter, the entire perception and control pipeline must respond in less than 90 milliseconds to maintain safe operation. This is crucial for avoiding potential collisions or other dangerous situations, especially in dynamic environments such as urban traffic.

Autonomous decision-making: Which is related to this, According to the research conducted by Ayvaz and Cetin [5], in complex and potentially ambiguous scenarios decision-making remains essential and an ongoing area of debate, it also discusses the ethical challenges in no-win accident scenarios, where autonomous vehicles may have to make difficult choices about the least harmful course of action. According to Hussain [28], the decision-making process in autonomous vehicles is informed by predictions based on sensory data, which is processed alongside inputs from other modules. The final decision is made after considering multiple factors, ensuring that the vehicle chooses the most appropriate course of action in real-time.

Environmental perception: Another crucial requirement for safe AV operations is reliable environmental perception, which allows the vehicle to navigate by comprehending its surroundings. One of the primary issues in designing a perception system, according to Babaei et al. [6], is making sure that different environmental factors, like moving and static obstructions, traffic signals, and road conditions, are reliably and precisely detected. Badué et al. [7] give a thorough summary of the perception subsystems commonly found in autonomous cars. These subsystems are in charge of several functions, such as road mapping, vehicle localization, tracking and detecting moving objects, and mapping static obstacles. An attention-based neural network created to manage the complexity of driving surroundings is presented by Zhang et al. [63]. Their model improves the capacity of the perception system to prioritize important information from the vast sensory data available, allowing the vehicle to focus on the most relevant obstacles and road conditions.

Object detection and tracking multiple objects: According to Venugopala et al.[57], autonomous vehicles can navigate complex environments by accurately identifying and tracking multiple objects in real time, making them fundamental to the vehicle's perception and decision-making processes. According to Yurtsever et al. [61], identifying static objects (from traffic lights and signs to road crossings) and dynamic objects(other vehicles, pedestrians, and cyclists) is important. Dynamic object tracking plays an essential role in the perception system of autonomous vehicles, enabling them to anticipate and react to the movements of other objects in the environment, such as pedestrians, vehicles, and obstacles.

Dynamic object tracking: According to Nabati et al. [44], Dynamic object tracking is necessary for crucial tasks like path planning and obstacle avoidance. Recent advances in multi-sensor fusion, including the combination of radar and camera data, have improved the performance of dynamic object tracking systems. Object detection is of 2 types, 2D and 3D. Recent advances in multi-sensor fusion, including the combination of radar and camera data, have improved the performance of dynamic object tracking systems.

2D object detection: Arnold et al. [3] point out that datasets like KITTI have introduced specific challenges to 2D object detection by providing real-world driving scenarios that demand high accuracy. 2D methods offer fast detection capabilities and can effectively identify objects such as vehicles, pedestrians, and traffic signs. However, they are unable to provide the in-depth information required for driving tasks such as path planning, collision avoidance, and so on.

3D object detection: 3D object detection on the other hand, addresses the shortcomings of 2D detection by incorporating depth information, allowing the vehicle to understand the exact position and size of objects in the real world. Alaba et al. [2] note, that 3D object detection has become a cornerstone in autonomous driving, providing enhanced environmental comprehension. The integration of LiDAR, radar, and stereo vision sensors has facilitated significant progress in this area, allowing self-driving cars to more reliably detect and track objects in three-dimensional space. Arnold et al.[3] state that, when 2d detects objects on the image plane, 3D introduces a third dimension to the localization, size regression, and revealing depth information in world coordinates.

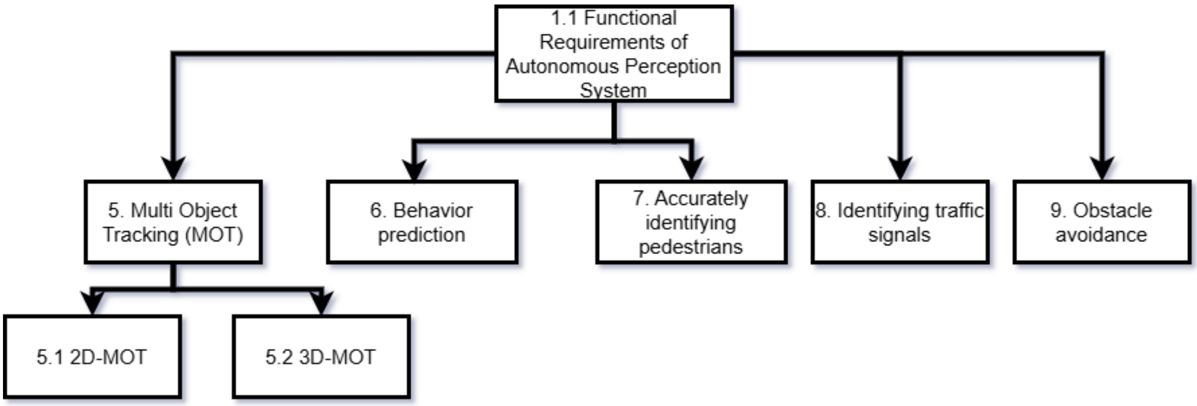

Figure 3.2: Functional requirements in AV perception system

Multi-object tracking (MOT): is another crucial aspect that enables the vehicle to track multiple objects simultaneously. As Nabati et al. [44] describe, MOT systems analyze video frames to identify and track objects in the environment, often without prior knowledge about the appearance or number of targets. It is crucial for self-driving cars to monitor cars, pedestrians, cyclists, and other road users at the same time. The figure 3.2 shows the other functional requirements

2D-MOT: Nabati et al. [44] highlight the effectiveness of 2D-MOT for analyzing video data but note that its limitations necessitate the use of additional sensors to provide a complete understanding of the environment. It does not provide in-depth information. In 2D multi-object tracking (2D-MOT), the tracking is performed on a 2D plane, typically using camera images.

3D-MOT systems: Weng et al. [59] claim that 3D-MOT systems track objects more precisely and without the perspective distortion that frequently affects 2D systems because they use input detections from 3D sensors like LiDAR and radar. By adding in-depth information, 3D multi-object tracking (3D-MOT) expands on the capabilities of 2D-MOT. This allows the system to track objects in 3D space and gives a precise estimation of object motion and appearance in 3D. The precision of 3D-MOT systems has been improved by the merging of radar and camera fusion techniques, which has allowed autonomous cars to perceive and respond to their environment more accurately.

Behavior prediction: is another requirement in autonomous vehicle perception systems. Babaei et al. [6] emphasize that autonomous vehicle perception systems must not only detect objects but also predict behaviors and environmental changes. This predictive capability is vital for proactive safety measures, such as anticipating potential collisions or predicting lane changes by other vehicles. Behavior prediction is critical for autonomous vehicles to operate in dynamic environments, to anticipate the movements of other road users, and to take appropriate actions.

Accurately identifying pedestrians: Autonomous vehicles must also be capable of accurately identifying pedestrians in or near their path to ensure safe navigation, particularly in urban environments where pedestrian activity is high. Parekh et al. [46] note that pedestrian recognition consists of multiple stages: segmentation, feature extraction, segment categorization, and track categorization. Each of these stages contributes to detecting pedestrians and predicting their movements based on environmental factors such as traffic signals, road conditions, and the behavior of nearby vehicles.

Identifying and interpreting traffic signals: enables us to follow traffic laws and navigate intersections safely. According to Kuutti et al. [34], the perception system continuously evaluates the driving environment to detect traffic signals, road users, and obstacles. Traffic signal recognition is particularly challenging in complex urban environments where signals can be occluded by large vehicles or buildings.

Obstacle avoidance: According to Laghmara et al. [35], Obstacle avoidance can be done based on 3 steps: perception, path planning, and control guidance. Dynamic obstacle detection is done based on an evidential occupancy grid. Then, a smooth trajectory is created based on the sigmoid function to avoid the detected obstacle.

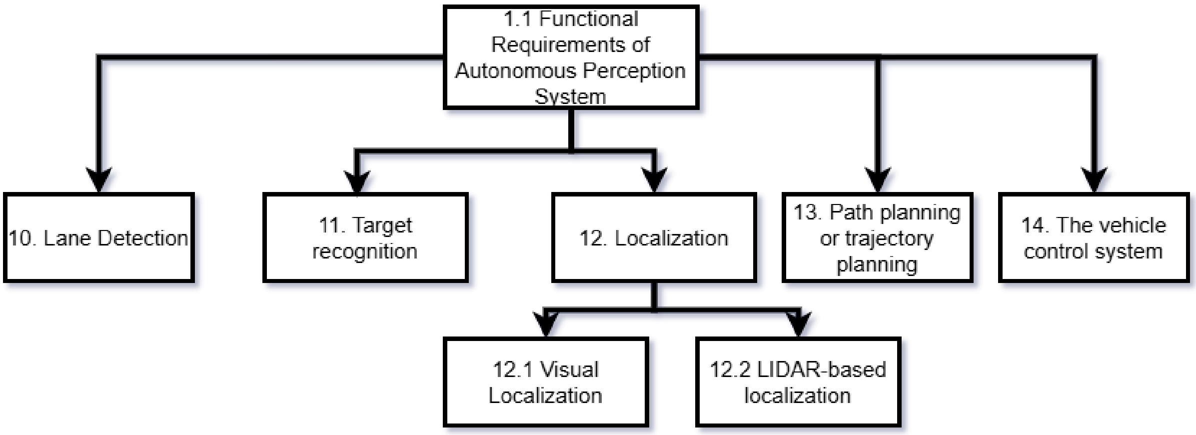

Figure 3.3: Functional requirements of AV perception system

Lane detection: Wang et al. [58] emphasize that lane detection guarantees the safety of driver less operation by maintaining the vehicle in its assigned lane and avoiding accidental lane departures. Modern lane detection systems rely on camera-based systems that use image processing algorithms to detect lane markings. See figure 3.3

Target recognition: As noted by Wang et al. [58], datasets like KITTI have played a significant role in advancing the field of target recognition by providing standardized benchmarks for evaluating algorithms in autonomous driving scenarios. KITTI enables the evaluation of stereo images, optical flow, visual ranging, and 3D object detection, which are essential for target recognition tasks.

Localization: It enables the vehicle to identify its position and orientation within its environment. According to Babaei et al. [6], localization integrates various sensors like GPS, GNSS, LiDAR, IMU, and RTK to accurately determine the vehicle's location on a global coordinate system. Kuutti et al. [34] also emphasized that the localization system is crucial in identifying the ego-vehicle's position and orientation for safe navigation.

Visual localization:, as described by Wang et al. [58], leverages monocular cameras for six-degree-of-freedom (6-DOF) repositioning, using deep learning techniques like Bayesian convolutional neural networks to regress the pose of a 6-DOF camera from a single-RGB image.

LiDAR-based localization: Wang et al.,[58] also describe LiDAR-based localization started before visual localization, which has been used extensively for environmental awareness in self-driving cars to complement radar, cameras, and ultrasonic sensors. However, it remains sensitive to adverse weather conditions like rain and fog.

Path planning, or trajectory planning:, is another essential aspect of autonomous driving. According to Parekh et al. [46], onboard sensors such as LiDAR, cameras, GPS, radar, and inertial sensors feed data into the path-planning algorithm to ensure safe and efficient navigation. Kuutti et al. [34] further describe that path planning is closely tied to the outputs of the perception and localization systems, influencing decisions such as lane changes, speed adjustments, and obstacle avoidance. Recent advancements in path planning focus on real-time decision-making and dynamic environments. For example, Parekh et al. [46] discuss how machine learning models can now analyze real-time sensor data to predict future road conditions and behaviors, improving the vehicle's ability to plan safe trajectories.

The vehicle control system: must execute precise vehicle maneuvers, including steering, braking, and acceleration. According to the research of Kuutti et al. [34], vehicle control systems translate high-level behavioral plans into actionable commands (steering, accelerating, and braking). Control accuracy is dependent on localization quality, as any errors in positioning can directly impact the control system's ability to make safe, real-time adjustments to vehicle actions.

Priori mapping: It is a method that many modern autonomous systems employ, where detailed 3D maps of the environment are pre-built and stored for reference during navigation. According to Van Brummelen et al. [56], companies like Google and Uber rely on these high-definition (HD) maps to achieve centimeter-level accuracy in localization. These maps contain detailed information, including road geometry, landmarks, and traffic signs, which helps AVs navigate complex urban areas more reliably. See figure 3.4

Sensor fusion: A key component of AV perception is sensor fusion, which integrates information from multiple sources to produce a cohesive and precise picture of the vehicle's surroundings. According to Babaei et al. [6], the overall dependability of the perception system is improved by combining data from several sensors, including cameras, LiDAR, radar, and ultrasonic sensors. The limits of individual sensors are reduced via sensor

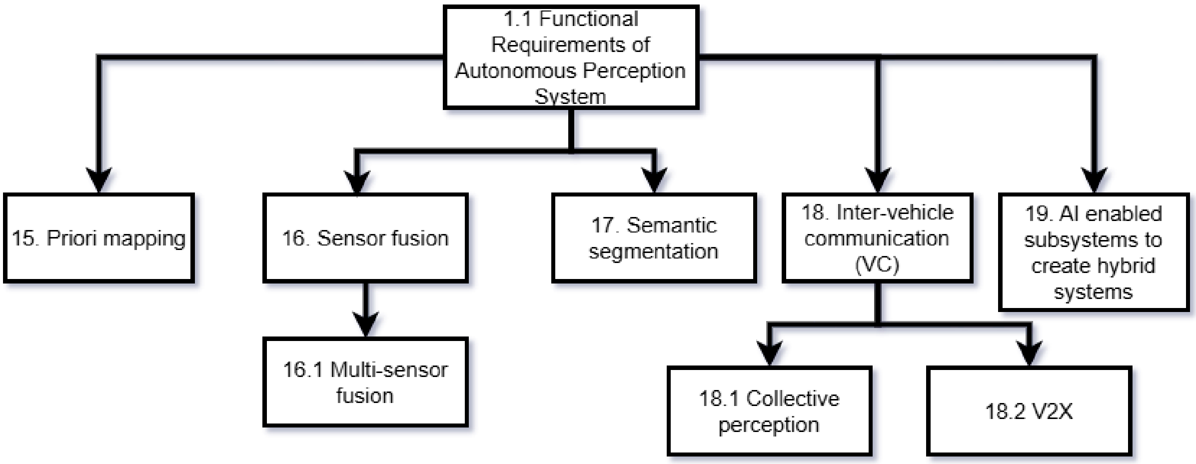

Figure 3.4: Functional requirements of AV perception system

fusion; for example, cameras offer rich visual data, whereas LiDAR provides accurate distance measurements but may not function well in bad weather (Yeong et al., [60].

Multi-sensor fusion According to Yeong et al. [60], to address the limitations of individual sensor types, multi-sensor fusion is crucial and increases the system's overall dependability and efficiency. Labeling every component in the driving environment is another essential task in AV perception systems, which provides pixel-level picture knowledge. It facilitates a more thorough understanding of the scene. According to Feng et al.,[16], dividing a scene into multiple significant elements, like roads, cars, pedestrians, and other obstructions, is important.

Semantic segmentation: Babaei et al. [6] emphasize that semantic segmentation (pixel-level segmentation) gives each pixel in an image a semantic label. The author proposes that the car can identify and comprehend important aspects of its surroundings, such as lane markings, road boundaries, and other vehicles, it also predicts the class, shape, and position of the objects.

Inter-vehicle communication (IVC): plays a pivotal role in enabling cooperative behavior among autonomous and ordinary vehicles, pedestrians, and other road users. Hussain and Zeadally [28] highlight that vehicles will not only share raw data such as location or speed but also more sophisticated insights like perception and driving decisions. This cooperative crowd-sensing enables vehicles to collaborate in real time, enriching their decision-making processes and enhancing safety.

Collective perception: Lobato et al. [39] describe how collective perception aims to aggregate sensory data from multiple vehicles to create a broader field of view. By pooling data from surrounding vehicles, the system enhances obstacle detection and prediction, enabling Connected and Autonomous Vehicles (CAVs) to navigate more efficiently and safely. Expanding on inter-vehicle communication, the concept of collective perception systems (CPS) is a crucial development for CAVs.

V2X:(Vehicle to Everything) As per the research of Yusuf et al., [62], V2X allows the sharing of information between autonomous vehicles and other road users; this includes V2V(vehicle to vehicle) and V2I(Vehicle to infrastructure). **AI and ML-enabled sub-**

systems to create hybrid systems: From the research of Rausch et al., [48] modern autonomous systems combine AI-based subsystems with traditional engineering techniques to create hybrid systems that can make more complex, context-aware decisions. With the help of these ML models, AVs can continuously learn from massive amounts of data, enhancing their capacity to identify and react to various traffic conditions.ML and AI are key components of AV technology.

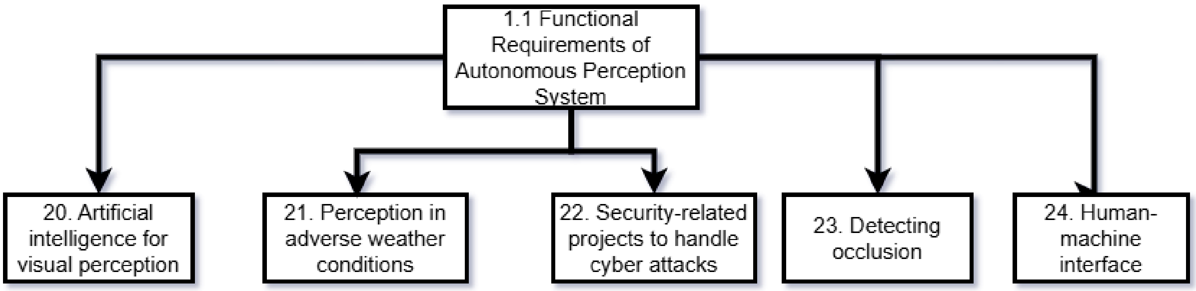

Figure 3.5: Functional requirements of AV perception system

Artificial intelligence for visual perception: Developments in artificial intelligence and deep learning for visual perception have driven recent advances in the technology of autonomous vehicles. A thorough review of the main deep-learning techniques used in autonomous driving systems is given by Grigorescu et al. [20]. Because of their capacity to process spatial input, Convolutional Neural Networks (CNNs) are frequently employed for visual perception tasks like object detection and lane tracking. Conversely, recurrent neural networks (RNNs) are used to forecast pedestrian and vehicle movements. By allowing cars to learn the best driving techniques through trial and error in dynamic conditions, Deep Reinforcement Learning (DRL) improves decision-making abilities.

Perception in adverse weather conditions: As noted by Van Brummelen et al. [56], vision-based and LIDAR systems can be severely impacted by environmental factors such as snow, rain, or fog. Snow, in particular, can obscure lane markings, which many AVs rely on for navigation. This is a significant challenge in AV, ensuring reliable perception in adverse weather conditions.

Security-related projects to handle cyberattacks: With the increasing complexity of AVs, cybersecurity has become a growing concern. Parekh et al. [46] state that modern vehicles incorporate a range of sensors, actuators, and communication systems that could be vulnerable to cyberattacks. This increases the chances of cyberattacks, and several security-related projects are conducted to handle cyberattacks. See the figure 3.5

Detecting occlusion: Venugopala et al. [57] discuss detecting occlusion, that a certain object blocks the view of another object which is in the view state of ego vehicles, resulting in invisibility or partial view of the object. It also describes how occlusion can distort sensor readings and create uncertainty in the perception of critical objects. To mitigate this, advanced algorithms and sensor fusion techniques are necessary to reconstruct occluded objects from partial data and maintain a clear understanding of the environment.

Human-machine interface: Human-machine interaction(HMI) is an interaction between humans and the vehicle; it helps the user(passengers and pedestrians) to understand what the system is doing. Morra et al., [43] state that Passengers need to feel confident all the time; they need to have information about the state of the vehicle, the environment, and the current behavior of the vehicle. Hence, HMI is profound and establishes a relationship between passengers and vehicles, so UX(User Experience) is considered most important.

3.2 Non-functional requirements

The development of the perception system in autonomous vehicles is made easier by a few evolving non-functional requirements. It comprises a number of important elements, including safety, robustness, and user acceptance etc (shown in the figure 3.6).

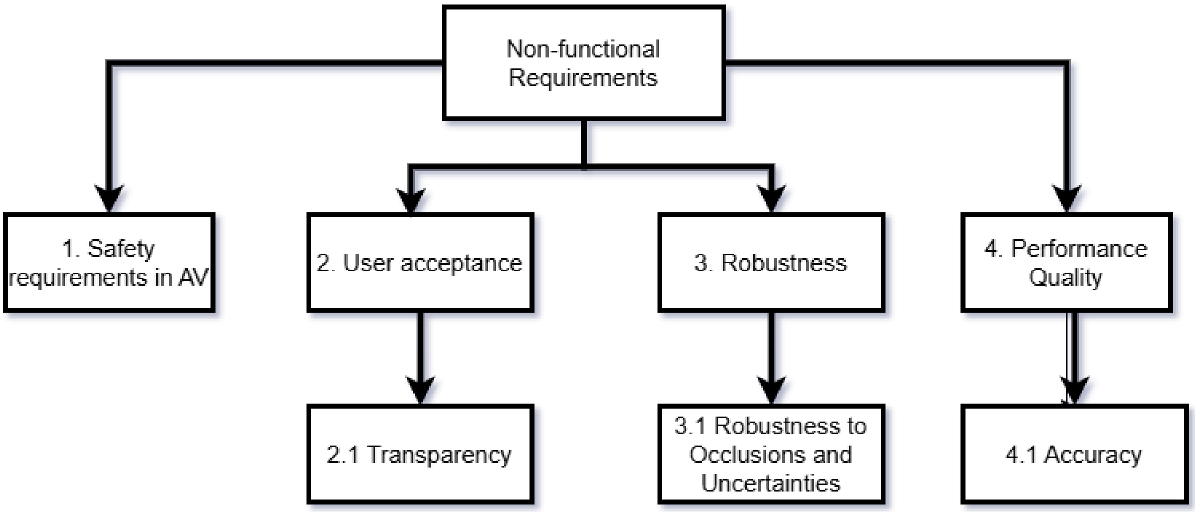

Figure 3.6: Non-functional requirements of AV perception system

Safety requirements in AV: Since human lives are on the line, safety is a primary concern in the development of autonomous vehicles. The ISO 26262 standard, which is specific to the electrical and electronic systems in passenger automobiles, was adopted by the automotive industry to guarantee high safety requirements. This standard, which is a modification of IEC 61508, focuses on functional safety, including standards for software quality, according to Rosique et al. [50]. For AV systems to operate properly in all circumstances, these criteria are essential throughout their whole life cycle. Hussain [28] further emphasizes that safety in AVs is a multidimensional issue, where maintaining human life and minimizing risks is critical.

User acceptance: Parekh et al. [46] highlight that many customers are still hesitant to embrace AVs due to concerns over safety, reliability, and the unproven nature of the technology. Increasing trust is essential for market acceptance, and this will require active involvement from governments and automotive manufacturers to address consumer concerns and enhance public perception of AVs. One of the significant problems in AV is the loss of consumer trust and acceptance..

Transparency: Parekh et al. [46] argue that another essential component of establishing trust is transparency. Transparency should be viewed as a non-functional necessity in the development of self-driving automobiles. Open communication about autonomous systems' operation and associated risks helps consumers to better understand the technology, which may increase its acceptability.

Robustness: Robustness is a key technical requirement for autonomous vehicles, particularly in challenging driving conditions. Kuutti et al. [34] underline that robustness ensures the AV can function reliably under a range of uncertainties, such as environmental challenges and sensor limitations. Autonomous vehicles must be able to localize themselves accurately, even in environments where road markings are absent or unclear and during harsh weather conditions like darkness and snow.

Robustness to occlusions and uncertainties: According to Hussain et al, [28], the prediction will be affected by occlusive and uncertain environments. These issues arise when objects or obstacles block a vehicle's sensors or when the behavior of nearby objects, such as other cars, is unpredictable.

Performance quality: According to Rosique et al. [50], Rapid advancements in information, electronics, and communication technology like sensors and networking performance improve the development of autonomous vehicle technologies.

Accuracy and reliability: Venugopala [57] notes that to achieve accuracy and reliability, AVs are equipped with various sensors, including LiDAR, Radar, cameras, and ultrasonic sensors. These sensors enable the vehicle to detect objects, predict movements, and navigate its environment.

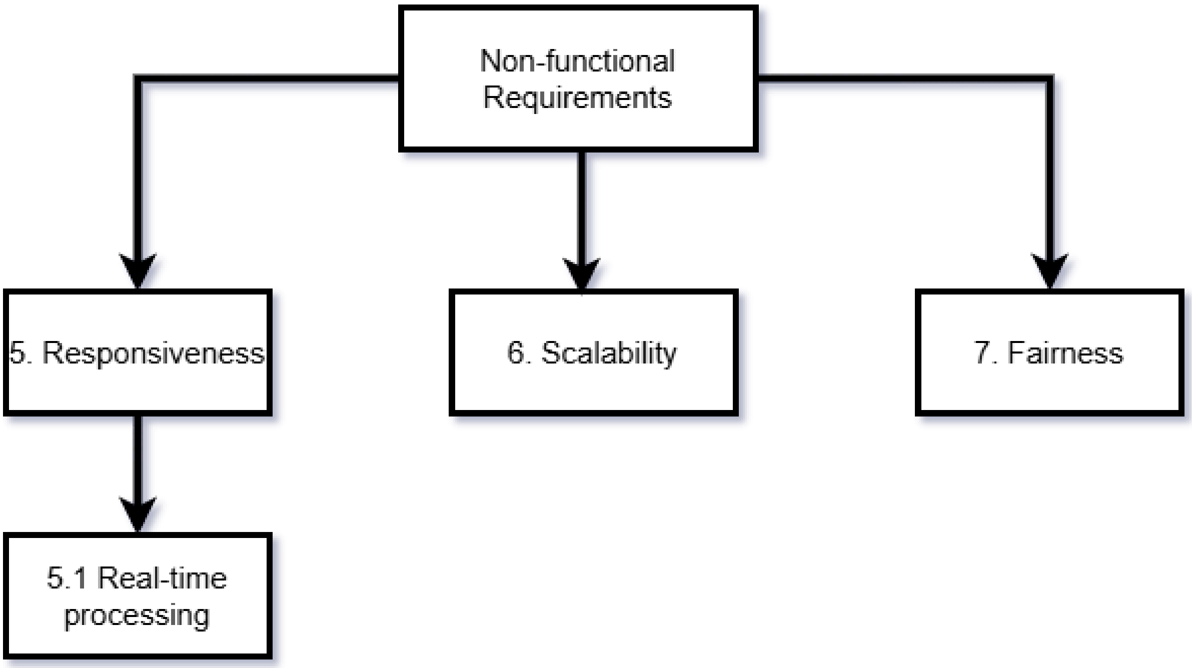

Figure 3.7: Non-functional requirements of AV perception system

Responsiveness: Purwanto et al. say that [47] Real-time responsiveness emerges as a pivotal theme. It emphasizes the safety, reliability, and efficiency of autonomous driving systems in real-world scenarios. Real-time response is important for AVs, as delays in perception could lead to accidents or other problems.

Scalability: Thandavarayan et al. [54] introduces the concept of scalable cooperative perception. Cooperative perception systems allow vehicles to share sensory information, expanding their field of view and improving decision-making. However, as more vehicles participate in this network, there is a need to reduce channel load and ensure the system remains scalable without sacrificing performance.

Fairness: Bonnefon says that [10] "Fairness requires that personal data collection, processing, uses, and outcomes do not discriminate negatively against any individual or group of data subjects. This entails that data-driven CAV operations should be as inclusive as possible."

3.3 Challenges in autonomous vehicle perception system

Despite significant advances, there are many common challenges in autonomous vehicle perception systems. In addition to that, the evolving requirements present many challenges stemming from the complexity of real-time data processing, the integration of diverse sensor modalities, and the need for robust decision-making capabilities through ML and AI.

3.3.1 Common challenges

Lack of real-world testing: Many AI-driven pedestrian and trajectory prediction methods are predominantly tested in simulated environments, limiting their applicability to real-world scenarios. Parekh et al. [46] highlight this issue in pedestrian detection, where no real-time experimentation is done to test a model's ability to classify objects effectively under real-world conditions. Complexities such as heavy obstructions and mismatches between a pedestrian's orientation and the image mask can result in errors during orientation estimation, reducing the accuracy of prediction in unpredictable, dynamic environments.

Ambiguity in multi-object tracking: Multi-object tracking is another critical challenge for autonomous driving systems. According to Babaei et al. [6], there are three major sources of ambiguity in this area: the number of objects, the time and location where objects appear or disappear, and the situation of those objects. These ambiguities make it difficult for perception systems to track and anticipate the movements of multiple entities accurately in complex traffic scenarios.

Adverse weather conditions According to Babaei et al. [6], the localization capabilities of onboard sensors are severely affected by unfavorable weather circumstances, including fog, snow, and darkness. These circumstances hinder perception systems' functionality, particularly in challenging driving situations like intersections. Since continuous and dependable sensing is essential to safety, this remains to be a major drawback of current autonomous vehicle technology.

Inefficiency of cyber security: Perception system cyber security is crucial since attacks on self-driving cars might have severe and dangerous effects. Babaei et al. [4]

emphasize that preserving the security and integrity of these systems is essential to the safe deployment of autonomous vehicles. This area's vulnerabilities could result in harmful interference, which could cause dangerous driving practices or system malfunctions.

Interpreting and comprehending sensor data: Once sensor data is captured, the next challenge lies in interpreting and comprehending this data. Babaei et al. [6] identify issues such as image interpretation, pattern recognition, and object detection as central to ensuring accurate real-time reactions to the vehicle's environment. Errors in processing and understanding this data can lead to incorrect decisions, further complicating autonomous driving.

Dealing with sensor limitations and uncertainties: Babaei et al., [6] describe that sensors used in perception systems have inherent limitations and uncertainties. Cameras, for instance, may suffer from a limited field of view or perform poorly in low-light conditions, while LiDAR sensors can struggle with detecting certain materials or have limited range. Radar sensors, on the other hand, may face difficulty distinguishing between closely placed objects. Wang et al. [58] also stress that sensors introduce uncertainties, which complicates the perception system's ability to make reliable decisions, since "what you see is not necessarily what you get."

Less robustness and reliability: Grigorescu et al. [21] note that these systems still exhibit higher error rates, which makes them unsuitable for widespread use in real-world traffic scenarios and commercial large-scale deployment, showing less robustness than a human driver. Achieving the level of reliability needed for autonomous vehicles to operate safely and effectively under diverse conditions remains a significant research challenge.

Multi-modal fusion challenges: To mitigate the limitations of individual sensors, multi-modal fusion combines data from various sensor types (e.g., cameras, LiDAR, and radar) to improve perception. Alaba et al. [2] point out that while this approach can reduce sensor limitations and provide complementary information, multi-modal fusion remains challenging due to differences in how sensors represent input data. Successfully integrating diverse sensor outputs is essential for creating a comprehensive, reliable view of the vehicle's surroundings.

Complex weather and lighting conditions: Hulse et al. [27] indicate that drivers—and, by extension, AVs—must respond to diverse parameters, including other vehicles, pedestrians, and road conditions, under these varying circumstances. Ensuring that AV perception systems can handle such variability remains an ongoing challenge. Autonomous vehicles must be able to handle complex environmental conditions, such as changing weather, lighting, and road surfaces, all while interacting with various road users.

Safety and mechanical failures: One of the main challenges to embracing self-driving car technologies is worries about safety. Rosique et al. [50] emphasize the potential consequences of mechanical failures, which may lead to crashes and pose serious safety risks. The high cost of such incidents and the associated risk to human life underscores the need for robust systems that can mitigate or avoid mechanical failure.

Verification Within Reasonable Timeframes: Testing autonomous vehicles in real-world scenarios is time-consuming and expensive. Rosique et al. [50] highlight the difficulty of accessing the expensive hardware and resources necessary to conduct empirical field tests within a reasonable time frame. This limits the ability of researchers and manufacturers to perform extensive safety verification before deploying AVs on public roads.

Handling a large volume of sensor data: Autonomous vehicles rely on a large array of sensors that generate vast amounts of data, including camera feeds, radar signals, and LiDAR readings. According to Cui et al. [13], processing this heterogeneous sensor data in real time is difficult due to the lack of a unified data format and the complexity of fusion algorithms. Efficient data processing is critical for ensuring that AVs can make timely and accurate decisions based on real-time inputs.

Gender and age differences in perception of AVs: User acceptance of autonomous vehicles varies by gender and age. Hulse et al. [27] found that males typically view AVs as less dangerous and hold a more favorable outlook on the technology than females do, who seek more detailed information before making decisions. Additionally, younger adults are more adept at processing complex, new information, which may influence their willingness to adopt AV technology.

Limited perception systems and occlusions: Mo et al. [42] and Nabati et al. [44] both note that situations such as tunnels, parking lots, and dense urban intersections present significant challenges.Real-world traffic scenarios, occlusions, and limited perception distances present a variety of the most frequently encountered challenges. Occlusions, such as obstacles that block the AV's sensors, can prevent accurate detection of pedestrians or other vehicles, leading to potential accidents. Perception systems in autonomous vehicles often struggle with occlusions and limited visibility in complex traffic environments.

3.3.2 The challenges arise from the evolving requirements

As autonomous vehicles advance toward real-world deployment, they face challenges that arise not just from technical limitations but from evolving requirements in their operating environment. These include the need for continuous learning and system updates, as AVs must adapt to novel scenarios and dynamic conditions that were not accounted for during initial training. Regulatory and ethical considerations also present evolving challenges, as societal expectations and legal standards shift, requiring AVs to align with changing norms and decision-making frameworks. Additionally, safety and validation testing must become increasingly rigorous to meet the growing complexity and criticality of AV functions. Together, these challenges reflect the necessity for perception systems to evolve alongside the external demands placed on autonomous technology.

Continuous learning and system updates: Autonomous vehicles encounter scenarios that may not have been anticipated during the initial training phase of their AI models. Wang et al. [58] highlight the importance of enabling continuous learning and system updates to improve perception capabilities and adapt to new challenges. This is especially important as autonomous vehicles are exposed to dynamic environments where unforeseen obstacles and novel situations arise regularly.

Regulatory and ethical considerations: There are significant ethical and regulatory issues with the use of autonomous vehicles. As Hulse et al.[16] explain, ethical dilemmas arise when AVs must make decisions involving potential casualties. For example, AVs may prioritize minimizing the number of casualties in a crash scenario, which could affect how the technology is viewed and accepted by the general population. For AVs to be widely accepted, ethical decision-making and regulatory compliance must be balanced.

Safety and validation testing: Since AVs are safety-critical systems, their validation and testing must be exhaustive. Hussain and Zeadally [28] stress the importance of mission-critical and safety-critical systems meeting stringent requirements through fine-tuned testing. Any decision made by the AV system software can directly affect human lives, making rigorous validation essential for ensuring safety and reliability.

3.4 Effects arise, due to these challenges

The evolving requirements of autonomous vehicle perception systems also bring challenges, which in turn lead to some effects. Some of the identified effects after the above challenges are discussed here.

High Perception system error rates: The high error rate of existing perception systems is one of the main obstacles to the broad use of AVs. The error rates of AV perception systems are too high for safe, widespread commercial deployment, as Grigorescu [21] pointed out. The robustness of human drivers is currently lacking in these systems, which compromises their reliability in actual traffic. AVs cannot meet the necessary safety standards for everyday use without significant improvements in perception accuracy.

Crashes and the cost of failure: Another possibility is mechanical failure, which could lead to serious accidents. Rosique et al. [31] highlighted that collisions not only pose significant safety issues but also result in high costs, both financial losses and human casualties. Ensuring that AVs can reliably avoid mechanical failures is crucial to gaining public trust and reducing the costs of incidents.

Scope of technology and risky behavior: Interestingly, the very technology designed to improve road safety may inadvertently encourage riskier behavior among certain drivers. Hulse et al. [27]found that personality types like sensation seekers may engage in more reckless driving when using autonomous vehicles, assuming that the vehicle's advanced safety systems will compensate for their risky behavior. This underscores the complexity of integrating AVs into traffic systems where human behavior can vary significantly.

Blind spots due to limited perception range: Despite advances in sensor technology, autonomous vehicles still suffer from limited perception ranges and blind spots, which can result in dangerous misjudgments. " Due to several features like sensor features, obstacle occlusion lighting conditions, and difficult weather, the vehicle's perception range is restricted. This leads to blind spots within the field of view and complicates the provision of comprehensive perception data for autonomous driving. For instance, the perception system of a Tesla Model X failed to recognize the white side of a turning tractor, mistaking it for the sky, which led to a fatal crash in 2016" (Cui et al., [13]). Such incidents highlight the need for more reliable sensor technologies that can detect objects under diverse environmental conditions.

Complex interactions and conflicts on the road: Hulse et al. [27] noted that these interactions increase the likelihood of conflicts, particularly in dynamic environments like busy city streets. AVs must be equipped with advanced algorithms capable of resolving such conflicts without causing accidents or disruptions to traffic flow. Autonomous vehicles must interact with a wide range of road users, including pedestrians, cyclists, and other vehicles, which can lead to complex and unpredictable situations.

Errors in orientation estimation: Perception errors, particularly in orientation estimation, present another significant challenge. Parekh et al. [46] pointed out that heavy obstructions can lead to mismatches between the perceived orientation of pedestrians and their actual movement, causing the AV to make incorrect decisions about how to react. Handling these errors is necessary for enhancing the precision of AV perception systems.

Increased development costs: Developing autonomous vehicles is a costly endeavor, particularly due to the complexity of the software and hardware systems involved. Hussain and Zeadally [28] estimated that the software for AV systems can account for up to 50% of the total development cost, with additional costs for ensuring safety, reliability, and robustness. These high costs could slow down the large-scale deployment of AVs, as manufacturers and consumers alike face steep financial barriers.

Increased computational demand: The perception systems used in AVs require significant computational power, particularly as input resolution increases and the complexity of traffic scenarios grows. Hsiao et al. [26] found that higher obstacle densities around AVs can lead to spikes in computational demand, which can strain in-vehicle processors and slow down decision-making. Meeting these computational challenges is critical to maintaining the real-time performance required for safe driving.

Road accidents due to sensor limitations: Lastly, sensor constraints still present serious threats to the safety of AVs. According to Venugopala [57], sensors are the main instruments that autonomous vehicles (AVs) use to collect environmental data, and any limitation in their capacity to perceive their environment can result in traffic accidents. This is particularly troublesome when visibility is impaired, like fog, intense rain, or dim lighting. In order to reduce accidents and enhance AV safety generally, reliable sensor technologies must be developed.

3.5 Methodologies to handle the evolving requirements

Agile methodology: Agile has emerged as a widely adopted methodology in AVPS development due to its ability to accommodate uncertainty and iterative feedback. It emphasizes continuous delivery, customer collaboration, and responsiveness to change—traits particularly valuable for perception system modules [14]. According to [23], teams developing AV perception components, such as object detection and sensor fusion, benefit from agile's iterative cycles and cross-functional team coordination. Frameworks such as

Scrum and SAFe (Scaled Agile Framework) are often used to manage both small-team agility and large-scale system integration.

Mix of existing and new method: Due to the need for both structured planning and flexibility, AVPS development often combines traditional Waterfall models with Agile techniques. According to Habibullah et al. [24], upfront requirements elicitation and system decomposition (top-down) are used in early phases, while component-level development often proceeds in an Agile iterative (bottom-up) fashion. This hybrid approach allows for stability in system architecture while retaining adaptability in rapidly evolving perception modules.

Lean product development Adapted from lean manufacturing, Lean Product Development (LPD) has been applied in autonomous vehicle projects to shorten development cycles and minimize waste. It emphasizes early feedback, simplicity in design, and cross-functional collaboration. According to Lazer et al. [36] note that LPD is particularly useful when developing perception systems where time-to-market pressures are high and the cost of unnecessary complexity is significant.

In comparison to the existing literature, this study uniquely addresses the evolving nature of both functional and non-functional requirements in autonomous vehicle perception systems (AVPS). While prior research has extensively explored only different requirements. Moreover, current research often separates challenges from their developmental context and rarely connects them to software engineering methods. This thesis fills that gap by adopting a holistic perspective that identifies and analyzes the dynamic evolution of AVPS requirements and their associated challenges and impacts. It integrates both technical and development-oriented views by examining how methodologies like agile and hybrid models can effectively respond to these evolving demands [23]. By proposing adaptive development practices, this research contributes a comprehensive framework that not only deepens understanding of AVPS dynamics but also provides practical guidance for engineering more reliable, safe, and adaptable autonomous vehicle systems.

4

Methods

I adopted the ABC frameworks of research methods in software engineering[53] to design the research methodology for the case study. This encompasses qualitative research methodology, gathering of data, and analysis of data through the thematic method. The ABC framework consists of three key elements: Activities (what is done), Bases (what supports the activities), and Context (where and why the activities take place). In this study, the 'Activities' involved planning, data collection through semi-structured interviews, and qualitative analysis. The 'Bases' included the interview guide, pilot testing, and theoretical grounding drawn from the research questions. The 'Context' was defined by the practical challenges and evolving requirements in the domain of autonomous vehicle perception systems.

4.1 Qualitative research methodology

The qualitative research methodology is selected due to its greater efficiency in examining complex and in-depth experiences of human beings and their perspectives in real-world scenarios. This approach is ideal when investigating processes and contextual factors involved in the study, and it delves deeply into the perspectives of professional experiences of practitioners [18]. This research method is significant because it aims to achieve a thorough understanding of the evolving requirements, challenges, effects, and methodologies related to autonomous vehicle perception systems. The figure 4.1 below shows the processes of the research method. The figure illustrates the research methodology

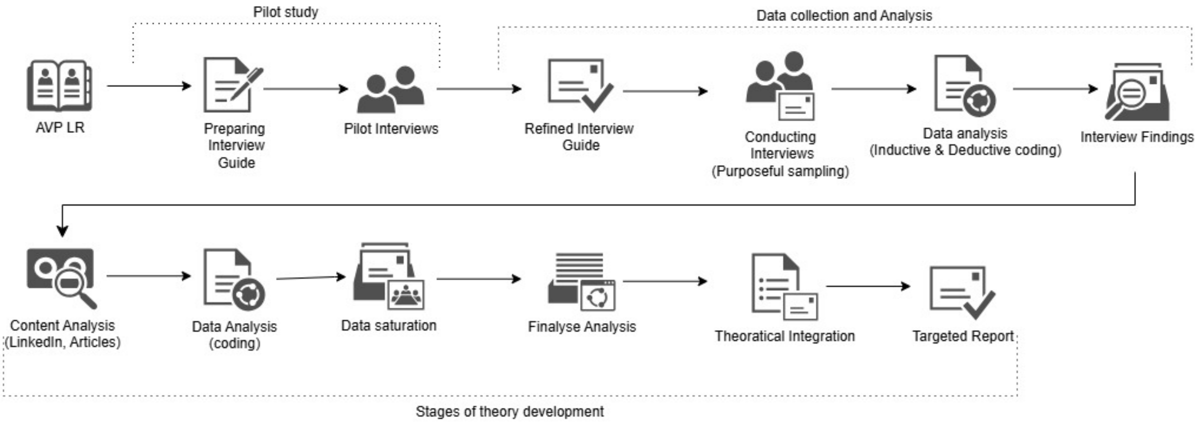

Figure 4.1: Research methodology:AVP LR(Autonomous vehicle perception system Literature Review)

adopted in this study, highlighting a structured and systematic approach to exploring the evolving requirements of autonomous vehicle (AV) perception systems. Beginning with qualitative research through an exploratory study, the process moves to the preparation phase, where purposeful sampling and a semi-structured interview guide were developed to align with five central research questions (RQs). The data collection phase involved conducting interviews and applying content analysis to capture in-depth insights. In the analysis phase, both inductive and deductive approaches were used to identify emerging. Finally, the reporting phase synthesizes the findings in relation to each RQ: RQ1 and RQ2 were addressed through questions on evolving functional and non-functional requirements; RQ3 explored challenges in perception systems; RQ4 examined consequences of these challenges; and RQ5 investigated how agile methodologies can mitigate evolving requirements. This structured process ensured comprehensive and evidence-based responses to all research objectives.

4.2 Preparing for data collection

RQ1: What are the most evolving functional requirements of autonomous vehicles' perception systems?	
1	What are the AV perception system's most critical functional requirements?
2	What advancements have been made in environmental perception for identifying static and dynamic obstacles in adverse weather conditions?
3	How do perception systems prioritize different elements of the environment in high-density traffic situations?
4	How do you handle real-time data processing and quick decision-making in AVP?
5	How do adverse weather conditions, such as rain or snow, impact the accuracy of lane detection systems?
6	What are the key challenges in enhancing inter-vehicle communication (IVC) or vehicle-to-everything (V2X) for autonomous vehicles, and how does it improve safety?
7	How does multi-sensor fusion work, such as combining radar and camera data?
RQ2: What are the most evolving non-functional requirements of the autonomous vehicle perception system?	
8	What are the most evolving non-functional requirements for the Autonomous vehicle perception system?
9	From your experience, what are the industry standards or frameworks for safety in AV?
10	What are the advancements and challenges in cybersecurity?
11	What advancements are necessary to ensure autonomous vehicle perception systems' accuracy and real-time processing capabilities in complex, dynamic environments?
12	What steps are taken to minimize risks to human life when developing the perception system for autonomous vehicles?

13	What strategies can be implemented to enhance the robustness of autonomous vehicle perception systems in challenging environments, such as poor weather conditions or unclear road markings?
14	How does continuous testing play a role in ensuring the perception system's reliability and safety?
RQ3: What are the challenges of autonomous vehicle perception systems, and what challenges arise due to the evolving requirements?	
15	What challenges arise due to the evolving requirements in autonomous vehicle perception systems, and in what ways are agile methodologies used to address challenges in perception system development?
16	What methods are being developed to bridge the gap between simulation-based and real-world testing for autonomous vehicle systems?
17	How do you ensure reliable localization and object detection when environmental factors resist sensors, such as during snowstorms or heavy rain?
18	How do you mitigate the impact of sensor uncertainty, particularly in situations where the environment is unclear or sensors have a limited range?
19	How do the increasing costs of AV development affect consumers, both in terms of pricing and accessibility?
RQ4: What are the consequences of challenges in the autonomous vehicle perception system?	
20	What are the consequences of these challenges in AV perception systems?
21	Are there particular types of errors or blind spots that often arise, and how do you address them?
22	What steps are being taken to reduce the high error rates in AV perception systems to make them safe for widespread commercial use?
23	What measures can be taken to avoid accidents caused by system or sensor failures in AVs?
24	How do AVs ensure smooth interactions with human-driven vehicles that may have unpredictable behaviours, without causing accidents or disrupting traffic flow?
25	How do you mitigate the risk of failures in the perception system that could lead to accidents or safety hazards?
RQ5: How do we mitigate the consequences or challenges of the evolving requirements of autonomous vehicle perception systems?	
27	What are the different methodologies used for the development of software in autonomous vehicle perception systems?
28	How does agile respond to evolving requirements and technical advancements?
29	What do you think about which agile practices (such as scrum and retrospectives) are more beneficial in the development of the AV perception system?
30	How can agile's iterative development process help to gradually improve the accuracy and safety of perception systems in AVs by allowing continuous refinement based on real-world feedback?

31	How can Agile teams use real-world testing feedback from users to identify blind spot issues and implement sensor improvements in shorter, manageable sprints?
32	Can agile's focus on constant testing and validation throughout the development lifecycle reduce the risk of mechanical failures in AV perception systems?

Table 4.1: Interview-guide

The following sections reveal the essential steps adopted to prepare for data collection and the interviewing processes. The primary document utilized as the interview guide (see the table above, 4.1) specified instructions for the interviewee and the questions to be answered; the questions were developed in accordance with the research questions. To ensure greater relevance and clarity, a structured interview guide was carefully designed and directly informed by the study's five core research questions (RQ). Each section of the guide corresponds to one RQ, enabling focused and systematic data gathering. Section A (RQ1) investigates the most evolving functional requirements of autonomous vehicle (AV) perception systems, such as obstacle detection, decision-making in dense traffic, sensor fusion, and inter-vehicle communication. Section B (RQ2) addresses key non-functional requirements, including safety standards, cybersecurity concerns, reliability, and accuracy under complex conditions. Section C (RQ3) explores the common challenges in AV and challenges that stem from these evolving requirements, with attention to testing limitations, sensor failures, and environmental uncertainties. Section D (RQ4) examines the broader consequences of these challenges, such as system errors, safety risks, and the impact on user trust and adoption. Finally, Section E (RQ5) focuses on the role of software development methodologies, especially Agile, in mitigating these issues through iterative processes, continuous testing, and real-world feedback. The qualitative data collected was significantly influenced by these preparatory elements in terms of its quality and direction.

4.2.1 Sampling

In this study, Purposeful sampling was used to choose participants for semi-structured interviews. A commonly applied strategy in qualitative research is to guarantee that the selected individuals can offer valuable and relevant insights.. Specifically, a maximum variation strategy [12] was adopted to capture diverse perspectives across roles and experiences within the field of perception systems, system design, requirements engineering, and system architecture in autonomous vehicle perception systems. The aim was to explore how functional and non-functional requirements are evolving deeply, the challenges associated with them, their impact, and the development methodologies used in practice. The selection of participants was based on their professional experience and willingness to take part. The recruitment process involved outreach via personal networks, social media like LinkedIn, and the assistance of supervisors and colleagues. Out of approximately 40 individuals contacted, 16 agreed to participate. The selected interviewees consisted of industrial persons, researchers, professors, and experts related to autonomous vehicles.

4.3 Data collection

Interviewee ID	Role	Company	Years of Experience
ID1	CEO	Zion Tech AB	17+
ID2	Software Engineer	Univrses	4
ID3	Senior Engineer	Polestar	13
ID4	Engineer	Kognic	5
ID5	Solution Architect	Volvo	13
ID6	Researcher	Gothenburg University	2+
ID7	Architect	Zenseact	4
ID8	ML Engineer	Cruise	5+
ID9	Engineer	Wabtec	6
ID10	Researcher	RISE	2+
ID11	Associate Professor	Halmstad University	7
ID12	Engineering Manager	Aptiv	17
ID13	System Designer	Zenseact	5+
ID14	Engineer	Capgemini	3
ID15	Test Architect	Volvo	5
ID16	Architect	Scania	13

Table 4.2: Interviewee details including role, company, and years of experience

Two types of data collection were used: interviews and content analysis. Interviews were the leading platform used for gathering information regarding all the research questions(RQ1, RQ2, RQ3, RQ4, and RQ5). Sixteen interviewees were selected from diverse industries and academic backgrounds; out of that, 14 represent various companies, namely, Volvo, Zenseact, Scania, Capgemini, Cruise, Univrses, Zion Tech AB, Polestar, Kognic, Wabtec, RISE Research Institute, and Aptiv. 2 Researchers represent Gothenburg University, and one professor from Halmstad University. For the detailed view, see the table 4.2 above. The other method, other than interviews, is content analysis, which is used to collect, categorize, and interpret data from online communities and research publications.

4.3.1 Interviews

The most popular technique for gathering data is conducting interviews. Interviews for this study are semi-structured, with the researcher generating an interview guide with pre-formulated questions in advance of the interview, but the questions can be modified or expanded during the conversation based on the knowledge and experience of the participant. The interview questions are structured to align directly with the five core research questions (RQs) of the study, grouped thematically into Sections A to E. Each section consists of 5 to 6 questions corresponding to a specific RQ, covering functional and non-functional requirements (RQ1 and RQ2), challenges and consequences of evolving needs (RQ3 and RQ4), and the role of development methodologies such as Agile in addressing these challenges (RQ5). This structured approach ensures the collection of rich, targeted qualitative data that directly supports the study's objectives. To ensure the clarity, relevance, and effectiveness of these questions, a pilot study was conducted with a colleague prior to the main data collection. This step helped refine the questions for better alignment with the research objectives. Before the interview began, the interviewee was asked to sign a consent form, which guarantees their identity and confidentiality. As per the request, the interviewees received the interview guide prior to the interview. The interviews are conducted in Teams and last between forty and sixty minutes. An adequate introduction to the objectives and processes is provided to the interviewee, and the interviewee's consent is obtained. to be recorded is provided at the beginning of the interview. For further data analysis, the participant is introduced correctly at the start of the interview, given the rules for the session, and asked if they are okay with the conversation being recorded. The interviews are recorded and transcribed for further procedures. Participants are selected according to their expertise and experience in the specific fields of etc.

4.3.2 Content analysis

This method helps to identify trends, innovations, challenges, methodologies, and shared knowledge within the preferred domain. Content analysis was selectively applied to complement and reinforce key insights gathered from interviews, rather than being used as a primary data collection method. External sources were used, including LinkedIn posts, journal articles, and technical blogs, to enhance the credibility and depth of the themes, where interview data alone could benefit from external validation or broader context. The data gathered through content analysis focused on specific research questions where additional perspectives were deemed beneficial for example, LinkedIn was used to highlight practitioner concerns about electronic or software failures (RQ4), journal articles were referenced to support discussions on real-time decision-making (RQ1) and cybersecurity risks (RQ3), and a relevant blog post was used to illustrate the concept of freestyle development as a software methodology (RQ5). This strategic use of content analysis allowed the study to capture broader industry discourse, reinforce participant claims, and deepen the thematic understanding of evolving challenges and methodologies in autonomous vehicle perception systems.

4.4 Data analysis

Qualitative data is examined using thematic analysis because of its flexibility and accessibility. This offers a strong foundation for analyzing and understanding the information from the interviews. This methodology involves a structured process of identifying, analyzing, organizing, and describing patterns or themes that emerge from the data, ultimately enabling a comprehensive and meaningful interpretation of the dataset. According to research by Lorelli S. Nowell et al., [45], six different phases are described in order to carry out a methodological approach to data analysis, and then the data was cleaned

4.4.1 Data familiarization

At the outset of the thematic evaluation, I started out by means of transcribing and anonymizing all interview data to protect participant confidentiality, a key aspect in ensuring ethical studies practice. Each transcript was then carefully reviewed to verify its accuracy, laying a reliable basis for further evaluation, and then the data was cleaned. According to Braun and Clarke's [11], I have gone through the data through multiple readings, allowing me to grasp both the explicit and underlying meanings within the content. This deep engagement helped us move beyond initial observations and begin recognizing recurring ideas and early patterns relevant to evolving functional and non-functional requirements, challenges, effects, and various development methodologies within the context of the Autonomous vehicle perception system. Each transcript was approached individually to capture unique insights, which were then mapped against the overarching research questions. Instead of using conventional qualitative software, I carried out coding manually using Excel spreadsheets and organized codes visually on MIRO boards. Although this added a layer of complexity due to the differing data formats, it also enabled a more interactive and flexible exploration of the emerging themes.

In case of content analysis, alongside interview transcription, I collected and reviewed relevant secondary sources such as journal articles, blog posts, and professional social media content. These were selected based on their relevance to specific research questions and were read multiple times to ensure a strong contextual understanding. This familiarization process allowed me to draw early connections between interview narratives and external expert perspectives.

4.4.2 Generation of initial codes

A systematic and mixed-method coding approach was applied to generate the initial codes, combining both deductive and inductive techniques. According to Braun and Clarke's [11] suggestion to treat each data item with equal attention and allow significant elements to surface, the familiarization phase played a crucial role in highlighting key patterns across the dataset. Before diving into the data, a set of focus areas was defined with the research objectives of autonomous vehicle perception systems. This formed the basis for deductive coding and initially resulted in 32 codes based on the interview guide. As the analysis progressed, inductive coding was incorporated to allow codes to emerge directly from the participants' responses. This approach ensured that data-driven insights—especially those reflecting the evolving functional and non-functional requirements, challenges, their impacts on system design, and various development methodologies—were accurately captured. Codes were derived from meaningful words, phrases, and expressions that revealed sensor fusion, communication, and various methodologies—all of which directly affect the quality and responsiveness of perception systems in autonomous vehicles. I used Excel sheets for detailed coding and MIRO boards for organizing and visualizing the codes. To enhance the credibility of the analysis, my supervisor was actively involved in the validation process, independently coded the same subset of the dataset, and agreed beforehand on the specific sections of the interview transcripts to be analyzed. Weekly meetings were conducted throughout the coding phase, discussing evolving insights and ensuring consistency in analytical decisions. This flexible arrangement was capable of accommodating various data formats and facilitating a coding process that was iterative and reflective in nature. The code book included emerging themes. This coding process ultimately served to identify not only the key development obstacles but also methodologies that could better support adaptive, efficient, and safe perception system development in autonomous vehicles.

For content analysis, during the initial coding phase, relevant sections from the secondary materials were also reviewed for meaningful expressions, technical terms, or observations that aligned with participant responses. These insights were manually coded and categorized using the same Excel sheet used for interview transcripts. The same coding procedure of the interview was followed for this method also. It helped to identify points of convergence between interview data and external discourse, especially around challenges like cybersecurity and effects like system failure.

4.4.3 Searching for themes

I began this phase with a comprehensive set of codes derived from the entire dataset. Prior to the thematic mapping process, I explored thematic analysis with inductive and deductive coding approaches. While deductive themes were guided by existing research on autonomous vehicle development and system design, the inductive process allowed unexpected insights to emerge directly from participant responses. To organize the codes meaningfully, I transferred them from Excel into a MIRO board, which enabled the visual clustering of similar codes. This helped illuminate relationships and intersections across different dimensions of the data. Clusters of related codes were grouped into preliminary sub-themes, each reflecting a shared conceptual pattern relevant to the evolving functional requirements, challenges, and methodologies in the autonomous vehicle perception system. Some themes corresponded directly with predefined research questions, while others emerged organically through inductive reasoning. Tools like Excel and MIRO were instrumental in refining these themes and sub-themes when necessary. Throughout this process, I ensured that no valuable insights were lost by storing outlier codes in a separate section, allowing room for later integration or reconsideration.

As part of content analysis, derived codes were incorporated into MIRO boards alongside those from interviews to explore how external insights validated, extended, or nuanced participant views. For example, a LinkedIn post highlighting software malfunction complemented interview data under the "Software failure" sub-theme.

4.4.4 Reviewing themes

In the reviewing and developing themes phase, I undertook a critical and iterative evaluation of the initial themes, focusing on how effectively they represented the coded data and aligned with the overarching research questions. This step involved reassessing both individual codes and their grouping into sub-themes, followed by examining how these sub-themes contributed to broader thematic narratives. Consistent with Braun and Clarke's approach, I ensured coherence within and across themes while maintaining distinct boundaries to avoid overlap. During this phase, some themes were refined for clarity, others were merged to reflect conceptual similarities, and a few were restructured to represent the underlying data patterns better. For instance, through careful analysis, I grouped related codes such as camera, LiDAR, radar, and sensor fusion under the sub-theme Evolving Technology, which comes under the evolving functional requirements. This approach of organizing codes into sub-themes allowed for a more nuanced understanding of the layered complexity within each research area. This structured yet flexible thematic development process ensured that all relevant aspects of the data were captured and synthesized into a coherent and meaningful framework.

In content analysis, as themes were critically reviewed and refined, content analysis served as an external benchmark to evaluate the robustness of emerging narratives. Literature and online content were revisited to ensure that the selected themes were both data-driven and grounded in broader industry and academic discussions.

4.4.5 Defining and naming themes

In this phase of the thematic analysis, I engaged in a rigorous process of refining, defining, and naming the identified themes to ensure each captured a clear and distinct aspect of the dataset. Guided by Braun and Clarke's recommendation, I aimed to strike a balance between specificity and cohesion, avoiding overly broad or fragmented themes. Each theme was carefully examined to identify its core meaning and relationship to the overall research objectives. The codes and sub-themes are interrelated and contribute to understanding the evolving requirements, challenges, effects, and mitigation strategies in the autonomous vehicle (AV) perception system domain. The final structure consisted of five overarching themes, encompassing a total of 17 subthemes and associated codes for each category.

In content analysis, the categories were systematically reviewed and refined from secondary sources, such as journal articles, blog posts, and LinkedIn discussions, to ensure they were conceptually aligned with the overarching research objectives. These sources were mapped to the same thematic structure developed from interview data, with particular emphasis on clarifying their relevance to challenges, consequences, and strategies. Each content-derived insight was analyzed for its thematic fit and distinctiveness, helping to validate and define five major themes and their associated sub-themes.

4.4.6 Creating the document

In the final stage of this study, the findings from interviews and content analysis were reported. The results of thematic analysis were synthesized into a case study report that detailed the identified themes, sub-themes, and their associated codes, capturing the evolving functional and non-functional requirements, challenges, consequences, and mitigation strategies within autonomous vehicle perception systems. The selected participant quotes were incorporated to strengthen interpretive clarity and illustrate the prevalence of themes. The report aimed to highlight how these interconnected elements influence system design and performance, as well as safety in real-world contexts. Taking into account both the interview data and existing literature, the discussion focused on key insights and highlighted the importance of tackling socio-technical complexities with adaptive development strategies such as Agile, SAFe, and hybrid models.

Thematic analysis played a central role in answering the research questions by uncovering recurring patterns and deep insights across both interview and content analysis data. Each of the five research questions was directly addressed through the identification of well-defined themes, sub-themes, and associated codes. For instance, in response to RQ1 (evolving functional requirements), the sub-theme evolving Technology revealed advancements in AI, ML, and sensor systems like LiDAR and camera fusion, illustrating how AV perception systems are increasingly reliant on intelligent algorithms and real-time data processing. Likewise, RQ4 (consequences) was answered through sub-themes like System Failure, where participants and external sources reported blind spot-related accidents and decision-making difficulties caused by software malfunction.

By using content analysis, integrating insights from external sources such as LinkedIn posts, peer-reviewed journal articles, and technical blogs, the study was able to broaden its perspective beyond the direct input of the interview participants. This approach enhanced the depth and reliability of the thematic analysis by validating and reinforcing participant claims through publicly available, domain-relevant discussions. For RQ1, journal articles supported insights on real-time decision-making needs; for RQ3, literature validated cybersecurity concerns raised by participants. A LinkedIn post illustrated real-world impacts of system failures relevant to RQ4, while a blog post enriched RQ5 by framing freestyle development as a flexible, adaptive approach. As a result, the research findings gained additional contextual strength, reflecting both individual experiences and broader industry discourse.

5

Results

This section presents the findings derived from a thematic analysis of evolving requirements in autonomous vehicle systems, structured around codes, sub-themes, and themes. RQ1 explores the evolving nature of functional requirements, highlighting sub-themes such as enhanced environmental perception, AI-enabled functionalities, and real-time data processing capabilities. RQ2 focuses on non-functional requirements, emphasizing safety, reliability, cybersecurity, and system scalability. RQ3 addresses the challenges that emerge from these evolving requirements, including increased development costs, sensor uncertainty, and compliance with stringent safety standards. The consequences of these challenges, RQ4, often manifest as reduced functionality, decision-making difficulties, and increased risk of accidents. Finally, RQ5 investigates the methodologies employed to mitigate these challenges, identifying approaches such as Agile, SAFe, hybrid models, and continuous testing and validation. Together, these themes provide a comprehensive understanding of the evolving requirements of autonomous vehicle development and the strategies adopted to address emerging complexities. The initial deductive codes from the interview guide stored in the code book are shown in the Appendix A.1 and A.2.

5.1 RQ1.What are the most evolving functional requirements of autonomous vehicle perception systems development??

The derived codes and themes of RQ1 are given in the table 5.1. This table is also expanded in a mind map of RQ1. See the figure 5.1. The table summarizes the evolving functional requirements (RQ1) in autonomous vehicle perception (AVP) systems, different codes grouped into key sub-themes such as evolving technology, customer-driven requirements, and real-time processing. The corresponding mind map diagram visually clusters these codes to show interrelationships and thematic hierarchies that support structured understanding of these complex functionalities.

5.1.1 Evolving technology (based on AI, ML & Deep learning)

The evolving landscape of autonomous vehicle technology is deeply rooted in advancements in artificial intelligence, machine learning, and deep learning, as outlined by various contributors. Across the interviews, there was a shared understanding that traditional rule-based systems are no longer sufficient to meet the complex demands of autonomous driving. Participants noted how perception systems now rely heavily on AI-driven mod-

Theme (RQ1): The most evolving functional requirements in AVP?		
Codes	**Sub-Themes**	**Details**
Software and algorithm enhancement (AI-enabled)	Evolving technology (based on AI, ML & deep learning)	Evolving technology relates to software and algorithm enhancement, advancement of sensors and evolving functionalities.
Advancements of sensors (Camera, LiDAR, radar, and sensor Fusion)		
Evolving basic functionalities (Environmental perception, object detection, lane tracking)		
Architecture and design	Customer-driven requirements	Architecture design, risk assessment strategies comes under customer driven requirements .
Risk assessment strategies		
Region-specific adaptation	Region-specific adaptation	Details regarding adaptation to different regions and environments.
Vehicle communication or Vehicle-to-Everything (V2X)	Communication and connectivity	Details related to V2X communication protocols and infrastructure support.
Computational improvements	Real-time data processing / Quick Decision-making	Details focusing on computational speed and real-time decision-making capabilities.

Table 5.1: Codes, Sub-Themes, Themes and Details for RQ1

els for tasks such as object detection, recognition, localization, and environmental understanding. 10 participants raised evolving technology as an evolving requirement. Machine learning, particularly deep learning, enables these systems to learn from vast datasets, improve accuracy over time, and adapt to new or rare driving scenarios. Several participants also emphasized the growing role of sensor fusion, which combines inputs from multiple sources, like LiDAR, radar, and cameras, to provide a richer, more reliable interpretation of the driving environment. These AI-powered capabilities not only enhance system intelligence but also contribute significantly to safety and efficiency. One participant summarized this perspective clearly: *"To be able to have a good perception system, you need to be able to track objects in a 3D world… and also make predictions.. not only tracking but also prediction… where is this object gonna be in a certain period of*

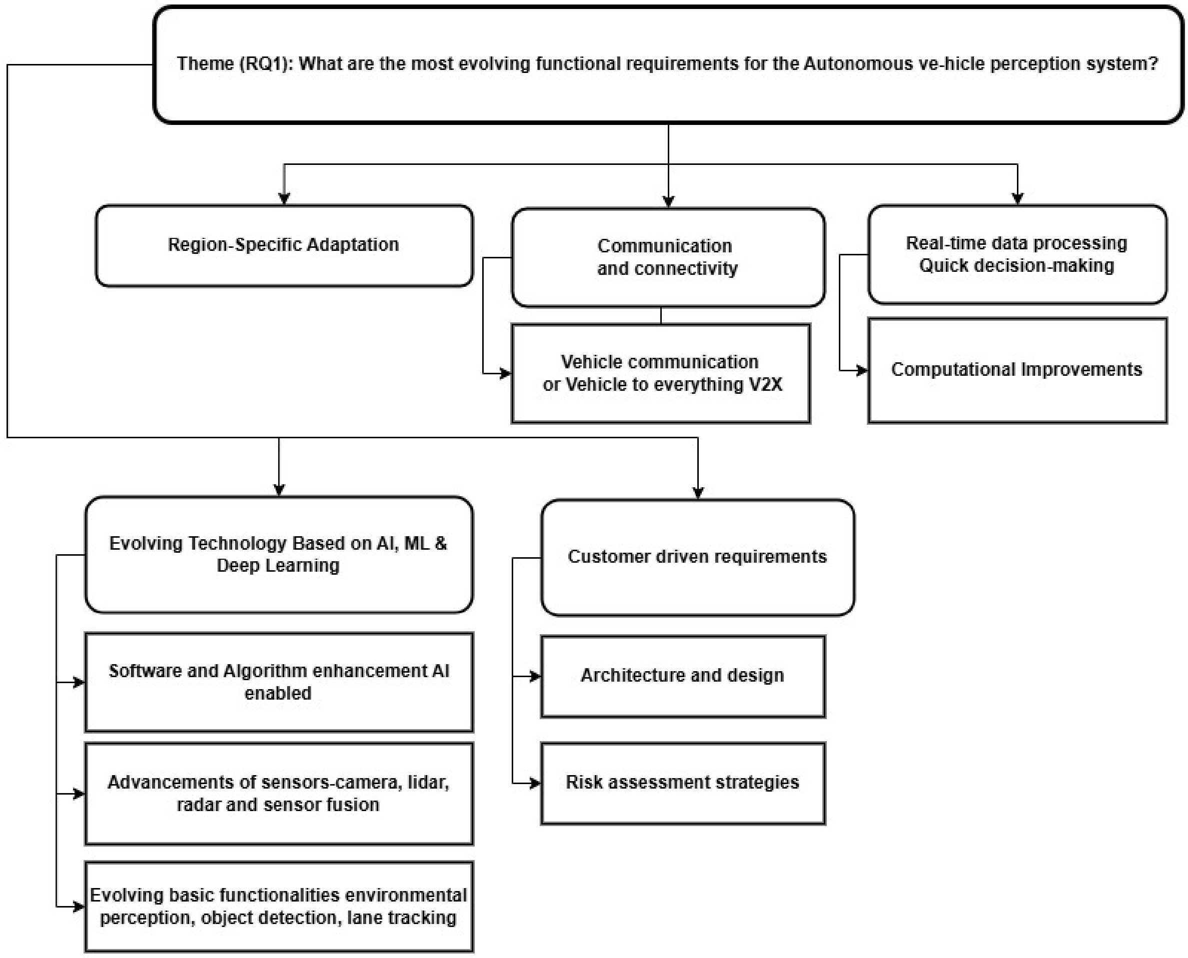

Figure 5.1: Mind map denoting RQ1

time?"(ID10). This viewpoint reflects a broader consensus that AI and its subfields are foundational to the next generation of autonomous systems.

5.1.1.1 Software and algorithm enhancement(AI enabled)

There is a shared understanding among participants that software and algorithm development is a key area where autonomous vehicle technology is evolving significantly. One common theme is the shift from traditional binary computing (using 0s and 1s) to future possibilities like quantum computing, which allows for vastly more complex data processing through the use of qubits. The integration of AI techniques such as deep learning, neural networks, and improved algorithmic logic is seen as crucial for enhancing core functionalities like object detection, lane detection, sensor fusion, and decision-making processes. This means evolving algorithms not only improve performance but also require robust revalidation to ensure they still meet safety and reliability standards. One of the participants has an implication directly related to this point *"You need to understand that software is becoming the key differentiator. Earlier, a lot of functionality was defined by hardware, but now, with AI and machine learning models, we are defining behavior through software updates. Even the same hardware can behave differently because of new software."* — (ID6). See the figure for the detailed view. 5.1

5.1.1.2 Advancements of sensors-camera, LiDAR, radar, and sensor fusion

Across the interviews, participants consistently highlighted the rapid advancements in sensor technologies—particularly cameras, LiDAR, and radar—as foundational to enhancing autonomous vehicle capabilities. Cameras are evolving toward higher resolutions like HD and 4K, enabling better low-light performance and image clarity, which is crucial for object detection in varying environmental conditions. LiDAR systems have seen major improvements, moving from mechanical to solid-state designs with extended range (300+ meters), offering highly accurate 3D mapping of surroundings. While some manufacturers lean toward camera-only systems, several experts emphasized the limitations of such approaches, especially under low-visibility conditions, and advocated for sensor fusion—integrating cameras, LiDAR, and radar for more reliable perception and decision-making. Radar, although not as detailed as LiDAR, remains valuable for detecting object speed and distance, especially in adverse weather. The consensus is that combining these sensors through AI-driven algorithms significantly enhances perception systems, enabling better object detection, localization, tracking, and predictive modeling. 8 participants highlighted this as an important evolving requirement. One interviewee described about this- *"For autonomous solutions, the trajectory needs careful planning with continuous feedback. We're moving beyond drive-by-wire systems, evolving hardware with new adaptive sensors like cameras, LiDAR, and thermal imaging."* —(ID1)

5.1.1.3 Evolving basic functionalities(environmental perception, object detection, lane tracking)

Participants described the importance of the evolving basic functionalities of autonomous vehicles, particularly in environmental perception, object detection, and lane tracking. Environmental perception helps vehicles detect objects and understand their surroundings, while object detection and lane tracking ensure accurate navigation. Sensor fusion, which combines data from cameras, LiDAR, and radar, is increasingly critical for reliable decision-making. An interviewee emphasizes, *"Perception systems require a combination of object detection, recognition, tracking, and prediction, with AI playing a key role,...."*(ID10)- highlighting the growing importance of AI in enhancing object recognition, tracking, and predicting behaviors in dynamic environments.

5.1.2 Customer driven requirements

Customer-driven requirements evolve continuously, especially in industries like automotive, where technologies such as autonomous vehicles drive significant changes. As emerging technologies develop, manufacturers often adjust to meet user expectations, such as improved safety or new features like in-car entertainment. However, these changes come with added costs, which must be weighed against customer willingness to pay for new functionalities. ID6 highlights that in autonomous vehicle development, requirements shift during the testing phase as more edge cases are encountered. Architecture and design considerations must also adapt, ensuring systems can integrate new features without compromising core functionalities. Risk assessment strategies are essential in these processes, as new technologies could introduce unforeseen challenges, demanding careful evaluation to mitigate potential safety concerns or performance issues. *"User expectation is broadly fixed. For example, you expect a car to start, be comfortable, and deploy airbags, but new expectations like watching Netflix or playing games can emerge as cus-*

tomer demands evolve." (ID9).

5.1.2.1 Architecture and design

The architecture and design of autonomous systems are undergoing significant transformation, driven by innovations across perception hardware, computational frameworks, and system integration strategies. Participants emphasized shifts from rigid, rule-based systems to more adaptive and situational aware architectures, including the adoption of end-to-end transformer-based models that handle perception and decision-making in a unified way. *“Hardware-wise, we need to break away from the drive-by-wire kind of architectures and move more into evolving architectures where you take decisions based on situations and then move into different lanes that are not going straight.”* – (ID1).

5.1.2.2 Risk assessment strategies

The evolution of autonomous systems not only involves architectural and technological changes but also demands a dynamic approach to risk assessment. As tools and methodologies shift—particularly with the integration of deep learning and AI—participants emphasized that traditional validation strategies must adapt accordingly. One participant explained it as *“Then, as the tools are evolving and as the methodology is changing, then the risk analysis will give different scores and based on that I think we will have to adapt our tooling testing strategies and develop strategies on that.”* – (ID2).

5.1.3 Region-specific adaptation

The evolving design of autonomous vehicles must account for region-specific adaptations, particularly in how sensor technologies align with local regulations and standards. Functional requirements such as sensor resolution, field of view, and computing capabilities are continuously being improved to meet these regional expectations. These adaptations are driven by evolving legal frameworks like Euro NCAP and differing homologation standards across countries. Although initial safety and testing standards were standardized, the development of these requirements now encompasses adjustments tailored to the unique challenges and traits of each region. *At the beginning, it was only Euro NCAP or NCAP sort of tests that were existing, right? Nowadays, we have started to see that these tests are being fine-tuned for each and every country, each and every region...*(ID12)

5.1.4 Communication and connectivity

Customer-driven requirements evolve continuously, especially in industries like automotive, where technologies such as autonomous vehicles and connectivity features drive significant changes. In the context of autonomous vehicles, connectivity tech- Technologies such as V2X (Vehicle-to-Everything) are becoming more crucial, allowing vehicles to exchange information with one another and the nearby infrastructure. The incorporation of technologies like Gen AI further accelerates this evolution, as manufacturers seek to integrate these capabilities into their systems to enhance communication and decision-making. The participant emphasizes *"In autonomous vehicle development, communication and connectivity are evolving with the increasing need for data exchange between vehicles and infrastructure. These advancements help improve system performance and reliability as more edge cases are encountered during testing."*-(ID6)

5.1.4.1 Vehicle communication or V2X

Communication plays a crucial role, particularly through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) technologies. Which improves safety and efficiency on the road. Vehicle communication can reduce latency in responding to changes in the driving environment by allowing vehicles to anticipate movements from other cars, reducing reaction times, and mitigating potential accidents. The European Union is actively driving the push for V2X communication standards, with ongoing research projects aiming to set guidelines for seamless communication between vehicles and infrastructure.10 participants specified about vehicle communication. *" V2X domain, which is still transitioning and not yet fully implemented in all vehicles. One key advancement I have noticed is that Gen AI is being integrated into most technologies, and suppliers are working to include it in what they supply to OEMs."*-(ID14)

5.1.5 Real-time data processing / Quick decision-making

Many interviewees responded regarding quick decision making, the evolving design of autonomous vehicles must account for real-time decision-making capabilities, especially in critical situations like sudden pedestrian detection. Latency requirements perform a vital role in ensuring that vehicles can react quickly enough to prevent accidents, with decisions needing to be made within hundreds of milliseconds between sensing and actuation. These requirements are calculated based on various speeds and potential obstacles, including how fast the vehicle can stop or avoid a collision.

Interview: One of the responses regarding this is *"The reaction time is calculated based on different scenarios, including speeds and how long it takes for the vehicle to stop, ensuring that these decisions are made in real-time..."* (ID6)

Content analysis: *"The vehicles need to build, monitor, and synthesize an internal representation of the environment around them. Then use this representation to formulate decisions and interact in an appropriate manner that respects the safety of the driver, avoids collisions."*-Article-[19]

5.1.5.1 Computational improvements

There is a consensus among participants that computational improvements perform an essential role in vehicle technologies, particularly in enhancing the decision-making processes and the vehicle's ability to respond in real time. Additionally, the shift toward more advanced computing paradigms like quantum computing is seen as a potential game-changer, allowing for more complex data processing and optimization of autonomous systems. One participant described it as follows: *"The thing about the software, software, and algorithm is that, OK, you move from binaries into quantum in the future..."* (ID1).

5.2 RQ2.What are the most evolving non-functional requirements of the autonomous vehicle perception systems development?

The derived codes and themes of RQ2 are given in the table 5.2. This table is also expanded in a mind map of RQ2. See the figure 5.2. This table presents the evolving non-functional requirements (RQ2) in autonomous vehicle perception (AVP) systems, emphasizing aspects like safety, system performance, and user trust. Sub-themes such as cybersecurity, reliability, scalability, and transparency are critical to ensuring that AV systems operate not only effectively but also securely. The mind map is the visualization of the same content.

Theme (RQ2): The most evolving non-functional requirements in AVP?		
Codes	**Sub-Themes**	**Details**
Cybersecurity	Safety	Ensuring system safety through cybersecurity and safety standards
Safety standards		
System performance	Reliability and robustness	System performance and accuracy depends on reliabilty and robustness
Data accuracy		
Transparency	User interface	Details about enhancing system transparency and trustworthiness
Trustworthiness		
Compatibility	Scalability	Details regarding system adaptability.

Table 5.2: Codes, Sub-Themes, and Details for RQ2

5.2.1 Safety

In the context of autonomous vehicles, safety is universally regarded as one of the most critical aspects. Various participants emphasize that safety is a broad and evolving requirement, with different facets contributing to the overall system's ability to operate securely and predictably in real-world conditions. The participant points out the continuous evolution of safety standards, which require vehicles to adapt to new data and scenarios to enhance their capabilities and prevent failures. This constant data collection and validation ensure that the vehicle's safety mechanisms are continuously tested. One participant states that *"Safety is definitely a crucial requirement. It involves that the vehicle be robust, work as intended, and be able to be resilient."*(ID6)

5.2.1.1 Cyber security

Cybersecurity is increasingly crucial in autonomous systems, as highlighted by some participants, who stress its importance in protecting against potential hacks that could alter system behavior. The growing attention to cybersecurity is necessary to ensure reliability and trust in autonomous vehicles. In essence, cybersecurity is a critical quality

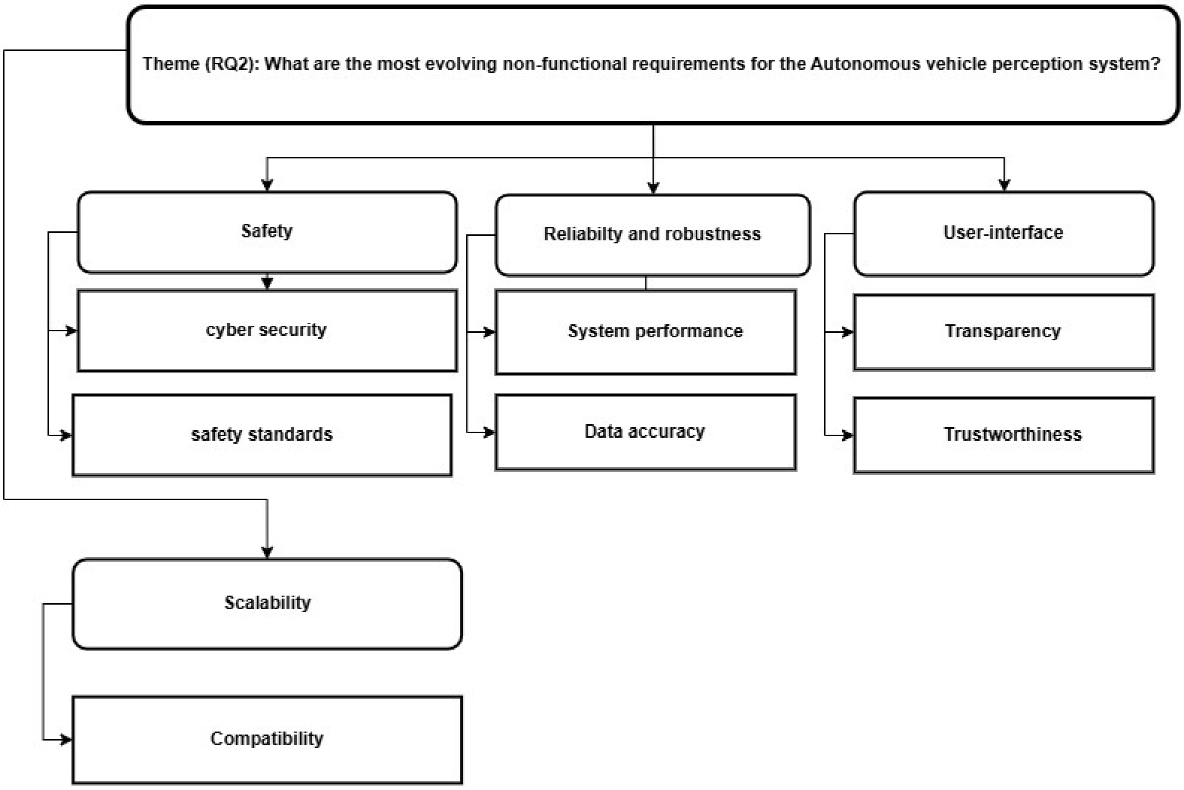

Figure 5.2: Mind map denoting RQ2

requirement, but its implementation may overlap with functional needs based on the specific needs of security measures. 8 participants raised their opinion on cybersecurity, as one of the Participant says it, *"Cybersecurity is getting quite more attention...deep learning models are known to, you know, could be manipulated in certain ways if certain weights are modified..."* (ID2)

5.2.1.2 Safety standards

The safety of autonomous vehicles is closely tied to adherence to various standards and regulations. More than 12 participants raised their valuable insights on safety standards. In addition to the SORTIF (Safety of the Intended Functionality) requirements, which focus on ensuring the robustness of systems under adverse conditions like bad weather or hazardous scenarios, other key standards include ISO 26262 for functional safety. This standard is fundamental in ensuring that the vehicle operates safely in all situations, especially when unforeseen events or malfunctions occur. Furthermore, ISO 21448 addresses the functional safety of the system in non-critical situations. As one participant highlighted, *"SORTIF actually stands for Safety of the Intended Functionality. So it describes how the intended function can behave in a hazardous way when there are adverse situations."* (ID16)

5.2.2 Reliability and robustness

Reliability and robustness are key pillars in the evolving landscape of autonomous vehicles, especially as customer expectations grow and vehicles operate in increasingly unpredictable environments. Robustness is not just about physical durability but also about ensuring consistent performance and fault tolerance when systems encounter edge cases or environmental challenges. At the same time, reliability ensures that the vehicle consistently performs its functions without failure, earning customer trust over time. 7 participants said about robustness. One participant says about it *"If you want me to rank or give one name, then I will say robustness, reliability—those are super important, even if it is working at 1 Hz, very slow speed."*-(ID11). See the figure for the detailed view. 5.2

5.2.2.1 System performance

Some participants place strong emphasis on performance from a machine learning standpoint, highlighting the importance of accuracy metrics across diverse environmental conditions—such as day, night, fog, or different types of road users—and the role of latency in determining model responsiveness. As participant puts it, *"The main requirement is to ensure that even if there is a regression, it is justified by an improvement somewhere else that may be more important,"* -ID8

5.2.2.2 Data accuracy

Participants discussed the critical role of accuracy in the performance of autonomous vehicles, particularly in tracking, threat assessment, and decision-making processes. Accuracy ensures that the vehicle can correctly identify and assess objects in its environment, especially when distinguishing potential threats. It is essential for determining whether a collision is imminent and ensuring appropriate actions are taken, such as braking. As one participant noted, *"The accuracy is calculated with all different scenarios, and then you take the worst scenario. You estimate the accuracy."* (ID5).

5.2.3 User-interface

Participants highlighted that the key aspect of the user experience is ensuring that the interaction with the system remains intuitive and less distracting for users. As autonomous vehicles progress, users will increasingly expect to focus less on the driving task and more on their personal activities, such as using their phone or preparing for meetings while traveling. The UI is designed to reduce distraction while still providing essential information and controls, creating a seamless balance between automation and user engagement. As one participant noted, *"People like to get more comfortable and they don't want to have less focus on driving, but more focus when they travel"* (ID5).

5.2.3.1 Transparency

Interviewees emphasized the importance of transparency in autonomous vehicle systems, particularly in the context of data transfer and system predictions. Ensuring that predictions made by the system are not only accurate but also explainable and understandable for end users is crucial for fostering trust and confidence in autonomous technologies. Transparency in data communication, including V2X (vehicle-to-Everything) interactions, is of the same importance to guarantee the quality and security of the transmitted information. As one participant highlighted, *"Ensuring security during data transfer and making predictions that are explainable and understandable for end users is also important"* (ID11),

5.2.3.2 Trustworthiness

Trustworthiness is a critical factor in the development and acceptance of autonomous vehicles. It is essential for developing public confidence that these systems are dependable and secure. Security concerns, particularly with the vulnerability of deep learning models to manipulation, make it even more important to address cybersecurity as a central focus. As one participant noted, *"Cyber security is getting quite more attention. And of course, reliability is one of the key aspects... to make them more reliable and in general increase the trust in the people as well"* (ID2).

5.2.4 Scalability

Participants are concerned that as technology advances, the introduction of more sensors and cloud integrations poses challenges for vehicle architectures to satisfy these developments. A major challenge is the capacity to handle and understand the huge amounts of data produced by these sensors. Moreover, the requirement for scalability encompasses the ability to adjust to new traffic situations and to guarantee that the vehicle's systems can manage complicated scenarios. One participant underlined this issue, remarking, *"The scalability aspect is a significant question. And how do you adjust to traffic conditions? Thus, I see these as areas that act as a kind of roadblock for scalability...*(ID1).

5.2.4.1 Compatibility

This involves taking into account the interoperability of various sensors, software packages, and communication systems like V2X, which enables vehicles to share information with one another and with infrastructure. It is also essential that these systems can be modular, making it easy to upgrade or adjust without affecting the overall system's functionality. One participant pointed out, *"Of course, compatibility issues also matter, like whether the things developed nowadays are compatible with existing hardware systems, computational systems on the vehicle, or modularity."* (ID11)

5.3 RQ3: What are the common challenges of autonomous vehicle perception systems development, and what challenges arise due to the evolving requirements in autonomous vehicle perception systems development?

The derived codes and themes of RQ3 are given in the table 5.3. This table is also expanded in a mind map of RQ3. See the figure 5.3. This table outlines the key challenges (RQ3) in AV perception systems, particularly those arising from technology advancement, increased complexity, and stricter safety expectations. As AV capabilities evolve, development costs rise, regulatory demands (e.g., ISO 26262) intensify, and sensor performance must remain reliable across unpredictable weather and operational conditions.

The analysis of interview data reveals a clear distinction between the common challenges faced in autonomous vehicle (AV) perception systems and those that emerge due

Theme (RQ3): Challenges due to evolving requirements in AVP		
Codes	**Sub-Themes**	**Details**
Increasing development cost	Technology advancement	Rising costs associated with high-performance sensors, hardware and different technology
Increasing number and complexity of requirements		
Sensor uncertainty and weather	Sensor uncertainty and weather	Environmental factors (fog, snow, rain) impact sensor performance.
Compliance with ISO-26262	Risk assessment and safety analysis	Adhering to evolving safety standards adds procedural and technical challenges, requiring rigorous validation for system safety.
Simulation-based and real-world testing		
Cyber security risks		

Table 5.3: Codes, Sub-Themes, and Details for RQ3

to evolving requirements. Common challenges are recurring technical and operational issues such as sensor uncertainty under varying weather conditions, the limitations of simulation-based testing compared to real-world scenarios, cybersecurity vulnerabilities, and the necessity to comply with safety standards like ISO 26262. These challenges are foundational and persist across different stages of AV development. On the other hand, challenges that come from changing requirements are driven by continual technological progress and changes in industry needs. These encompass the increasing number and complexity of system requirements, rising development costs, the necessity for continuous innovation, and more complex processes for risk assessment and safety analysis. Differentiating between these two categories of challenges provides a more structured understanding of the barriers encountered in AV development and helps in prioritizing solutions accordingly.

5.3.1 Technology advancement

Technology advancement becomes a challenge due to evolving requirements because, as the expectations for autonomous vehicle performance grow, such as higher levels of automation, enhanced safety, and better user experience, developers must continually upgrade sensors, algorithms, and computing infrastructure to meet these new demands. Participants gave their opinions about the continuous advancement of technology, which presented a significant challenge in the development of autonomous systems. As technology progresses, so do the demands on the system's capabilities. The integration of sensors, software, and hardware must evolve together to meet the needs of their opinions about the continuous advancement of technology, which presents the complexity of requirements. The constant need for technology updates and the integration of evolving features creates a moving target for developers, making it a significant challenge in au-

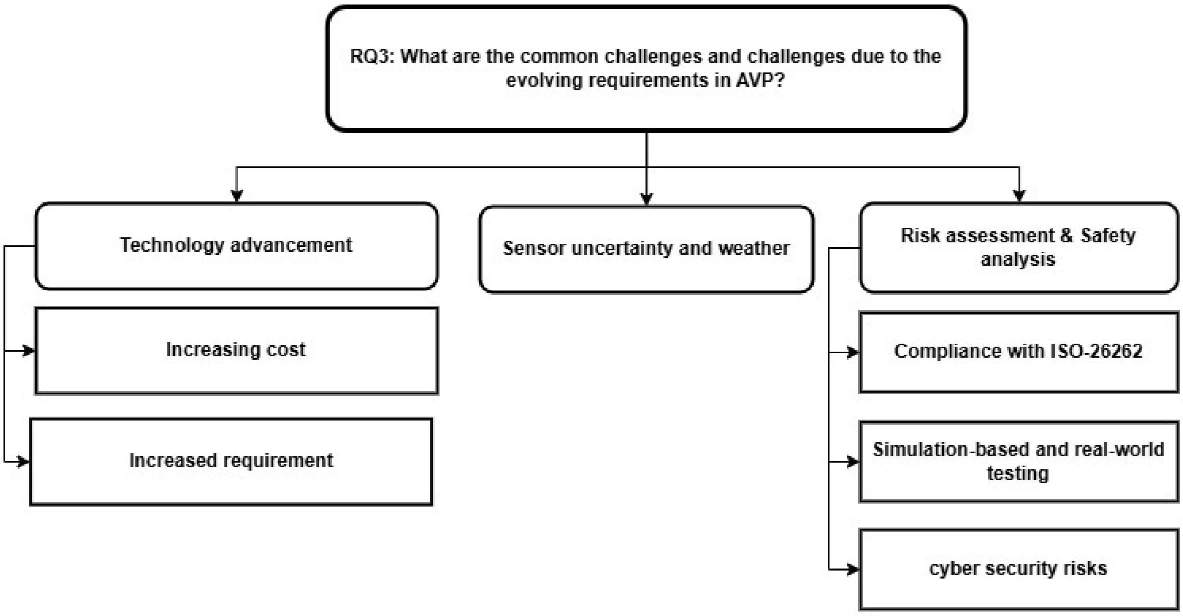

Figure 5.3: Mind map denoting RQ3

tonomous vehicle design. As one participant mentioned, *"The challenge is to innovate here. More and more requirements were put on ADAS feature functions or on the sensors, and that has brought them to this level of advancement."* (ID12).

5.3.1.1 Increasing number and complexity of requirements

As autonomous vehicle technology progresses, new functionalities, safety expectations, and regulatory standards continuously emerge. As technology evolves, the increasing complexity of requirements poses a significant challenge in the development of autonomous systems. As the number and complexity of requirements increase, development teams face challenges in simultaneously satisfying all constraints within limited time frames, hardware capabilities, and software architectures. With the rapid evolution of sensors and ADAS technologies, these requirements are continuously growing, forcing innovation to keep pace. The shift from basic systems like ACC to more advanced systems like L4 autonomy demands fulfilling much more stringent standards, such as ISO 26262, to ensure safety and functionality. One participant highlighted, *"The challenge is to innovate here... more and more requirements were put on ADAS feature functions or on the sensors, and that has brought them to this level of advancement..."* (ID12)

5.3.1.2 Increasing development cost

As the expectations for autonomous vehicle performance, safety, and compliance grow, so does the need for more advanced sensors, computing power, and complex software. Each new or updated requirement—such as improved perception accuracy, real-time processing, or stricter safety certifications—adds to the system complexity, thereby driving up development costs significantly. Most of the participants gave their opinion about the increasing development cost of the vehicle. In autonomous vehicle perception (AVP) systems, the increasing development costs driven by the need for advanced sensors, high-performance computing units, complex software algorithms, rigorous testing, and compliance with strict safety standards pose a significant challenge. As these vehicles require advanced hardware such as LiDAR, high-performance cameras, and powerful compute units, the overall production cost becomes substantial. Although the prices of components like LiDAR and cameras have decreased over the past decade, the complexity of autonomous systems continues to demand significant investment. This cost barrier has shifted the automotive industry toward new business models, such as subscription-based services, rather than traditional vehicle ownership. This shift not only addresses affordability but also accommodates the changing nature of vehicle usage in a more service-oriented society. One participant noted, *"The cost is high, but I don't think they are going to sell a Level 4 autonomous vehicle to a customer because the industry is transitioning towards more of a subscription-based system..."* (ID5).

5.3.2 Sensor uncertainty and weather

Sensor uncertainty and weather are common challenges in autonomous vehicle perception (AVP) systems because they directly affect the reliability of sensor data, which is foundational for perception. Interviewees responded on sensor uncertainty, which poses a critical challenge in the development of autonomous driving systems, particularly when safety-critical Decisions are made based on the accuracy and trustworthiness of the sensor data. In scenarios where data confidence is low, such as in poor weather conditions or when one sensor fails, functions like emergency braking may be disabled to avoid unsafe outcomes, while less critical actions like driver warnings may still be enabled. Sensor fusion plays a vital role in aggregating data from multiple sources to determine overall confidence levels, allowing systems to make informed decisions based on the quality of the combined input. 10 participants raised opinion on sensor uncertainty and weather. As one participant explains, *"We try to get this confidence level and depending upon that confidence level, we will enable or disable the intended functions... if the confidence is low, then we will be like completely disabling the function"* (ID16). See the figure for the detailed view 5.3

5.3.3 Risk assessment & Safety analysis

Each advancement in autonomy demands evaluation under a broader range of conditions. As new features and operational domains are introduced, the system must meet increasingly complex and stringent safety thresholds. Participants' concerns, as vehicles evolve toward higher levels of autonomy, are that ensuring that each feature functions safely across varying conditions becomes increasingly important. This is managed through rigorous safety assessments where risk levels are assigned to different scenarios, and if the system cannot meet the required safety threshold, it is restricted from operating in that context. This is where the concept of Operational Design Domains (ODDs) becomes essential, defining the specific environmental and operational conditions under which the vehicle can safely function. One participant emphasized this approach, stating, *"When the risk level is quite high enough... and if our system is not satisfying that level, then we would prefer... it won't be operating in this particular domain... Once we have reliable data... this feature can be another sort of operating domain" (ID2).*

5.3.3.1 Compliance with ISO-26262

This requires rigorous safety processes, documentation, and validation to ensure that every software and hardware component functions reliably in all conditions. Meeting these standards is essential to gain regulatory approval and public trust, yet it presents substantial technical and procedural hurdles for OEMs. The transition from lower-level autonomy, like Level 2 systems, to higher levels, such as Level 4, involves fulfilling far more stringent safety requirements, which is not a straightforward progression. As one interviewee explained, *"That's all the OEMs struggle... to show that we can do that and to not cause any accidents... a few years ago people thought... it's just the next step from pilot assist or L2 systems, but L4 system [has] much more requirements"* (ID5).

5.3.3.2 Simulation-based and real-world testing

Simulation-based and real-world testing is a common challenge in AVP because simulations cannot fully replicate the unpredictability and complexity of real-world driving environments. There is a shared understanding among participants that simulations offer a cost-effective, controlled space for early-stage testing, often using tools like Carla or custom OEM-built platforms, but they can only approximate the complexity of real-world driving conditions. The unpredictability and chaos of real environments—ranging from weather anomalies to human behavior—are difficult to fully replicate, which creates a persistent gap between simulation and practical deployment. This disparity raises concerns about whether systems that perform flawlessly in simulations can actually generalize to real roads. 15 participants said about this challenge, as one participant emphasized, *"If it doesn't pass at least the simulation, there's no point in doing it in the real world... there is definitely a gap between simulation and the real world, no matter what kind of system it is.."* (ID6).

5.3.3.3 Cyber security risks

Cybersecurity risks are a common challenge in AVP because autonomous vehicles rely heavily on software, connectivity, and data exchange, making them vulnerable to hacking, data breaches, and unauthorized control. Ensuring secure data transmission, safeguarding against unauthorized access, and building resilience against potential cyber attacks are now integral parts of vehicle design. With frequent software updates and added computing capabilities becoming standard, manufacturers must anticipate and mitigate evolving cybersecurity risks from the early design phases through to deployment. This includes not only protecting vehicle operations but also ensuring passenger safety and data privacy.

Interview: As one participant noted, *"the increasing risk of cyber security is also becoming... so that's also a part of the challenges that we will face..."* (ID16)

Content analysis: *" While AVs promise enhanced safety, efficiency, and convenience, they also introduce significant cybersecurity vulnerabilities due to their reliance on advanced electronics, connectivity, and artificial intelligence (AI). "* (Article-[15])

5.4 RQ4: What are the consequences of challenges in the autonomous vehicle perception system development?

The derived codes and themes of RQ4 are given in the table 5.4. This table is also expanded in a mind map of RQ4. See the figure 5.4. This table outlines key sub-themes related to challenges in autonomous or assisted driving systems. It highlights accidents caused by blind spots in perception systems, failures due to reduced functionality of electronics or software, and challenges in making accurate driving decisions. Each sub-theme addresses specific issues that impact the reliability and safety of these systems.

Theme (RQ4): Consequences/Effects		
Codes	**Sub-Themes**	**Details**
Blindspot	Accidents	Details regarding accidents caused by blind spots in perception systems.
Reduced Functionality	Electronic or software failure	Failures resulting from reduced system functionality.
Difficulty in decision making	Difficulty in decision making	Challenges in making accurate driving decisions.

Table 5.4: Codes, Sub-Themes, and Details for RQ4

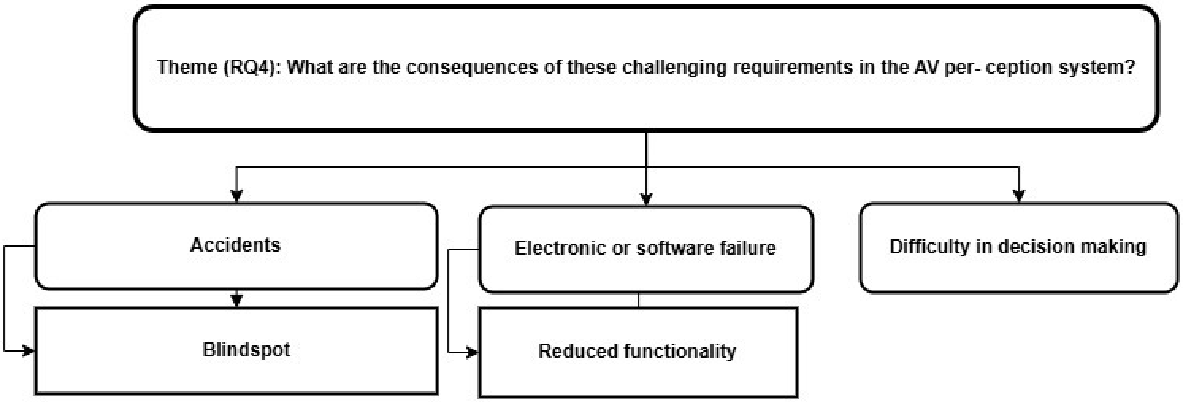

Figure 5.4: Mind map denoting RQ4

5.4.1 Accidents

Issues such as inadequate perception, unresolved blind spots, or system failures can all contribute to hazardous situations on the road. Ensuring safety requires thorough hazard analysis and precise sensor placement to eliminate blind spots that could otherwise go undetected and cause collisions. While premium vehicles may integrate enough technology to mitigate these risks, cost-effective models may lack the full range of safety features, increasing the potential for accidents. 3 interviewees reported their opinion on accidents.

As one participant emphasized, *“a robust perception is the critical thing... it should be a strong way of going towards a zero-accident code”* (ID11)

5.4.1.1 Blind spots

Blind spots can lead to critical safety risks, especially during interactions with other vehicles or vulnerable road users like cyclists. Addressing blind spots requires rigorous testing at various development stages—such as test tool trials (TT0, TT1, TT2)—and continuous feedback loops to ensure that undetected regions are identified and corrected before production. This iterative process includes simulation, test tracks, and real-world validation to catch false positives and false negatives early. Hazard analysis also plays a vital role in defining sensor placement to eliminate potential blind spots altogether. As one interviewee clearly stated, *“We don’t really have blind spots, at least not ones that could cause an accident... that comes from the hazard analysis”* (ID5).Refer the figure 5.4

5.4.2 Electronic or software failure

Electronic or software failures in autonomous systems can critically affect the performance and safety of the vehicle, making them a critical challenge to address. When such failures occur, there must be a mechanism in place to safely transition control back to the driver or bring the vehicle to a secure stop. This fallback mechanism, designed to either hand over control or ensure the vehicle reaches a safe location, is vital for preventing accidents. Ensuring that a single failure doesn’t compromise the entire perception system is another key challenge.

Interview: As one participant indicates, *“The main concern would be if that directly affects the performance of the perception system as a whole... You want to avoid a single failure affecting the whole system."* (ID10).

Content analysis- LinkedIn: Another thing denotes that *"A breach or malfunction in the software could lead to incorrect decisions, such as failing to stop for a pedestrian or misinterpreting road conditions"* (LinkedIn -Importance of secure software)

5.4.2.1 Reduced functionality

The absence of critical sensor systems or reduced capabilities in lower-cost models could result in safety risks. However, when budget constraints limit the inclusion of such sensors, the vehicle’s functionality may be compromised, leading to a large number of accidents or system failures. According to an interviewee, *"In the case of a cheaper vehicle, certain functionalities may not be available if blind spots exist,"* (ID5)

5.4.3 Difficulty in decision making

Decision-making in autonomous vehicles presents a significant challenge, particularly when trying to replicate human-like adaptability and judgment in complex driving environments. In addition, the difficulty of accounting for all possible scenarios complicates the decision-making algorithm. One of the interviewees says, *"Decision making is quite easy for you [humans], right? I mean, you see things beyond maybe 200–300 meters when* *you're driving on a highway...if we want to do them in an automated fashion, that is more difficult."* (ID12).

5.4.4 Causal Analysis for RQ3 and RQ4

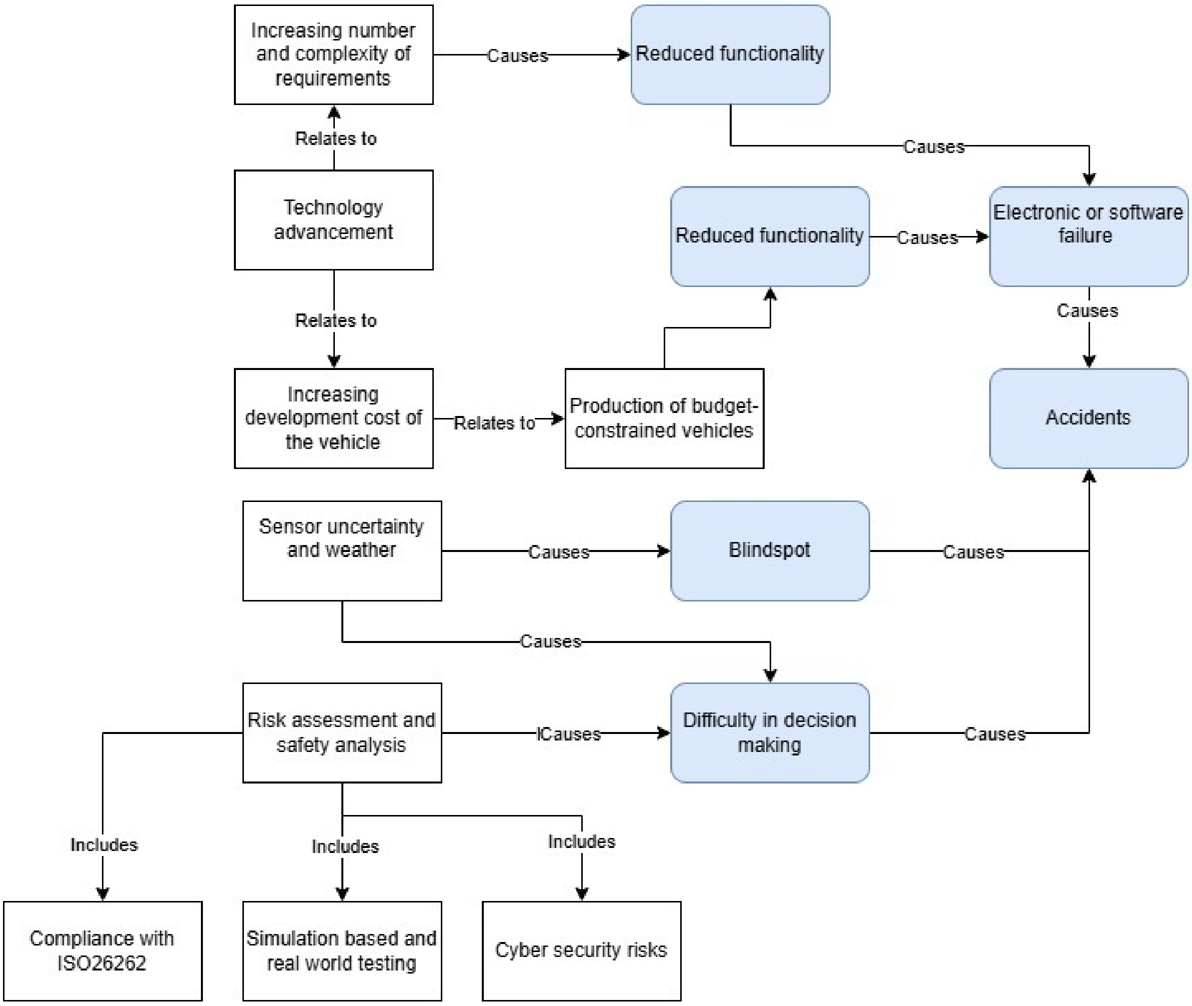

Figure 5.5: Cause-and-effect analysis of challenges and consequences in autonomous vehicle perception system development

The figure 5.5 presents a cause-and-effect analysis illustrating how key challenges in autonomous vehicle perception (AVP) systems (addressing RQ3-challenges-rectangle shape) lead to critical consequences (addressing RQ4-consequences-oval shape). It shows that technological advancement drives the increasing number and complexity of system requirements, which in turn lead to reduced functionality when the development process cannot keep up. This issue is further compounded by rising development costs, which are linked to the production of budget-constrained vehicles that may lack full sensor or processing capabilities, again contributing to reduced functionality. Reduced functionality is identified as a key factor leading to electronic or software failures, which can ultimately result in accidents. In parallel, sensor uncertainty and adverse weather conditions contribute to blind spots in the vehicle's perception, also increasing the likelihood of accidents. Risk assessment and safety analysis, which encompass compliance with ISO 26262, simulation-based testing, and cybersecurity risk management, influence the system's decision-making capabilities. When these mechanisms are strained or insufficient, the vehicle may experience decision-making difficulties, which is another factor contributing to system failure or unsafe operation. Collectively, this diagram clarifies how both evolving requirements and inherent system limitations culminate in severe effects such as electronic failure, blind spots, and accidents, thus supporting the analysis of RQ3 and RQ4.

5.5 RQ5: How do we mitigate the consequences or challenges of the evolving requirements of autonomous vehicle perception systems development?

The derived codes and themes of RQ5 are given in the table 5.5. This table is also expanded in a mind map of RQ5. See the figure 5.6. This table discusses various methodologies for mitigating challenges in development processes. It highlights the use of agile practices, particularly the SAFe framework, which emphasizes user feedback, constant validation, and flexible development cycles. Additionally, it explores hybrid development models, like SAFe or Waterfall combined with agile, and freestyle development approaches that allow for adaptive and flexible solutions. The mind map describes the same concepts like table.

Theme (RQ5): Mitigating challenges with methodologies		
Codes	**Sub-Themes**	**Details**
SAFe	Agile	Mitigating challenges by applying agile practices such as SAFe framework, incorporating user feedback, constant validation, and flexible development cycles.
Feedback from users		
Agile practices		
Constant testing and validation		
SAFe/Waterfall+Agile	Hybrid/Mixed Method	Using hybrid development models (like SAFe or waterfall with agile).
V-model+Agile		
Freestyle development	Free style development	Flexible, adaptive development approach

Table 5.5: Codes, Sub-Themes, and Details for RQ5

5.5.1 Agile

As per the shared opinion from the participants, agile methodology has increasingly been adopted in the automotive industry to address the evolving nature of requirements, particularly in software-driven development. Total of 16 participants explicitly mentioned agile or agile related methodologies. Unlike the traditional waterfall model, agile allows for iterative development, allowing teams to react swiftly to changing functional and customer needs. However, its application in hardware systems is more limited due to the fixed nature of physical components that require long-term planning. While agile offers

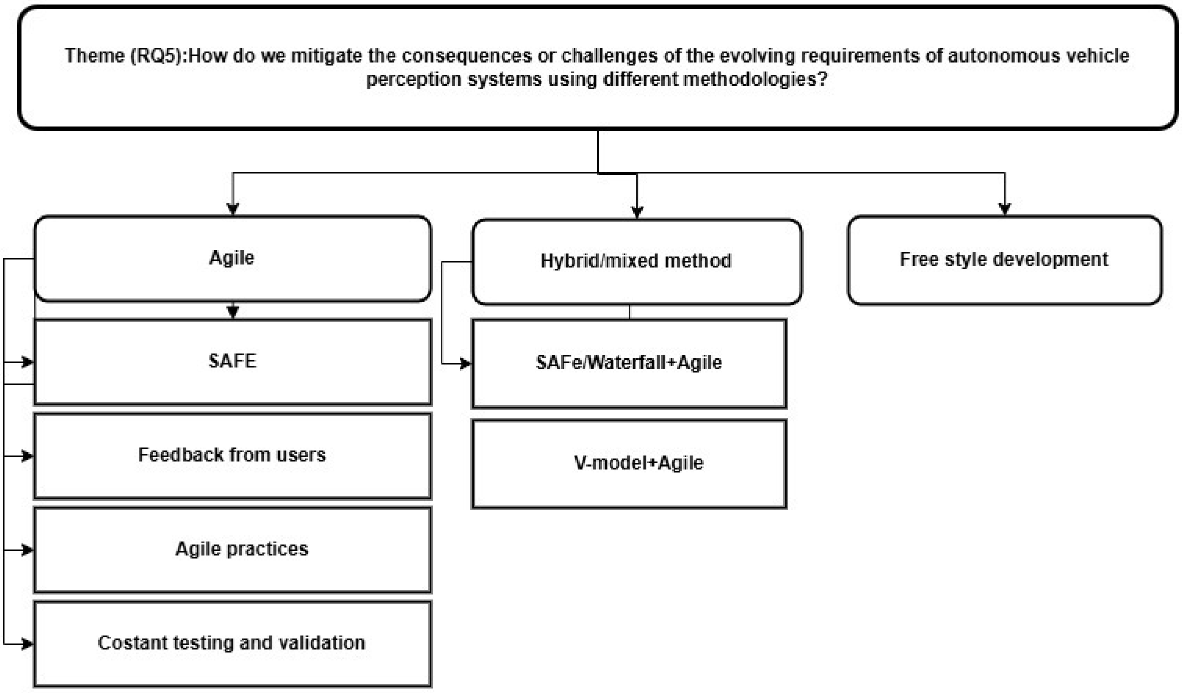

Figure 5.6: Mind map denoting RQ5

continuous improvement and adaptability, its success largely depends on team structure, communication, and project type. As a participant notes, *“It’s purely a software-oriented methodology... hardware changes can’t be fulfilled in the sprints process,...”* (ID3). See figure 5.6.

5.5.1.1 SAFe

SAFe (Scaled Agile Framework) has emerged in large development teams working on intricate systems like those in the automotive domain. It allows for coordinated, iterative progress across teams while maintaining alignment with organizational goals and safety regulations. By integrating agile principles at scale, SAFe accommodates continuous updates, feedback loops, and cross-functional collaboration—key needs in a rapidly changing technological environment. Still, strict regulatory boundaries, especially in safety-critical applications, mean that software changes post-approval must undergo rigorous checks and certifications. One participant highlights *“Once this is approved, we should not make software changes randomly... we need to get approval for any software we plan to release”* (ID3)

5.5.1.2 Feedback from users

According to the opinion of many participants, by analyzing logs, Diagnostic Trouble Codes (DTCs), and predictive maintenance alerts, engineers can gain insights into system behaviors under varied conditions and refine features accordingly. This feedback loop becomes increasingly valuable with successive product generations, where lessons from earlier iterations inform design improvements. Moreover, validation of non-functional requirements—such as usability, robustness, and performance—often depends on direct input from end users. One participant notes *"For validation, you need the main stake-*

holders, the user.. There is a discrepancy that needs to be investigated and solved...” (ID1)

5.5.1.3 Agile practices

Agile practices, particularly in large-scale implementations like Scrum and Scaled Agile Framework (SAFe), offer a flexible methodology for addressing the challenges posed by evolving requirements in automotive development. These practices emphasize continuous planning, iterative progress, and frequent communication, which help teams remain responsive to changing needs. By incorporating tools such as Kanban boards and focus groups and facilitating regular stand-ups, retrospectives, and burn-down charts, teams can adapt quickly to new insights and shifting priorities. As one participant notes, *"Most of the automotive manufacturers, autonomous manufacturers tend to work in agile environments... they have their own reasons why not to [adopt it]... but agile is the most widely adopted for now."* (ID6).

5.5.1.4 Constant testing and validation

From the opinion of many participants, by embedding practices such as continuous integration (CI), continuous development (CD), and verification into the agile framework, teams can ensure that each code iteration is tested thoroughly and incrementally. This ongoing process not only helps in detecting issues early but also supports quicker adaptation to changing customer or regulatory demands without compromising system integrity or safety. One participant says about it, *"it’s good to have this testing built into the CI/CD workflow because you can make changes much faster while being fairly sure that what you’re doing doesn’t break anything.."* (ID13)

5.5.2 Hybrid/mixed method

The hybrid or mixed methodology combines elements from both Agile and Waterfall approaches to address the challenges posed by evolving requirements, especially in industries like automotive development, where both hardware and software need to be integrated seamlessly. Agile allows for flexibility and adaptation as requirements change, particularly for software components, while the Waterfall model provides the structured planning necessary for hardware development. 5 people mentioned about hybrid method. One participant states that,*"Moving from agile into something more hybrid... makes sense? Maybe we need a new methodology."* (ID10)

5.5.2.1 Waterfall/ SAFe with agile

Agile faces challenges when applied to hardware systems, such as ECUs in vehicles. To overcome this limitation, a combination of Agile with Waterfall or SAFe is often used. SAFe, with its structured approach to scaling Agile practices across large teams, can help manage the complexity of hardware and software integration, ensuring that both are developed in parallel while maintaining clear plans for hardware specifications. *"Currently, it needs a mix of both waterfall and SAFe with Agile because, while software industries use Agile, on the other hand, there needs to be a plan to develop and integrate hardware into the car. So, yeah, we need both...* (ID3)

5.5.2.2 V-model+Agile

By combining the V-model and Agile frameworks, a special approach can be developed to address the particular requirements of industries such as automotive, where hardware and software development are both important. While Agile is known for its flexibility and iterative development, allowing for continuous feedback and adaptation, the V-model complements it by providing a structured approach to testing and validation. One participant said about it *"Some steps from the V-model can supplement Agile...companies might follow Agile, but it will be their way of Agile."* (ID16)

5.5.3 Free style development

Unlike the structured, heavy weight methodologies favored by some OEMs, this freestyle approach operates in a fast-paced environment where planning is minimal and flexible, with teams reacting to problems as they arise. where teams adjust dynamically to new challenges without getting bogged down by detailed documentation or strict adherence to processes. The tools, like JIRA, are still used but in a supportive, lightweight way to track progress, identify blockers, and maintain an overarching understanding of the team's work, rather than as the central focus of the development process.

Interview: According to a participant, *" I mean, it's some sort of freestyle thing, like with costs and interaction with your colleagues..."* (ID8)

Content analysis: *"Freestyle development is when you just have a blank text file and an idea, and you go make something out of nothing. This is the way to get started to make dreams a reality..."* -(Blog -Free style development)

6

Discussion

This section presents a detailed discussion of the findings derived from the thematic analysis, aligned with the five research questions that guided this study. Drawing on rich insights from participant interviews and supported by relevant literature, the discussion explores the evolving nature of functional and non-functional requirements in autonomous vehicle (AV) perception systems. It further studies the challenges posed by these dynamic requirements, the consequences, and the applicability of various development methodologies that arise. This section also describes the future works and threats to validity.

6.1 (RQ1):What are the most evolving functional requirements of autonomous vehicle perception systems development?

Evolving technology in autonomous vehicles (AVs): driven by AI, ML, and deep learning: I have seen many functional requirements in section 5.1 as described already. Findings from the results denote that the evolving technology in autonomous vehicles (AVs), driven by AI, ML, and deep learning, is reshaping core functionalities like object detection, tracking, and environmental perception. Traditional rule-based systems are insufficient, pushing the shift toward AI-powered models for better accuracy and adaptability, confirms the findings of Babaei et al. [6] and Badué et al. [7], who highlight the necessity of accurate environmental perception and the role of perception subsystems in navigation and obstacle avoidance. The importance of software and algorithm enhancements, particularly AI-driven behavior updates and future quantum computing, aligns with Rausch et al. [48]. Advancements in sensors, including high-resolution cameras, LiDAR, and radar, as well as sensor fusion, are crucial for reliable perception, echoing Alaba et al. [2] and Yeong et al. [60], who emphasize multi-sensor fusion as vital to environmental comprehension. Additionally, improving basic functionalities like 2D/3D object detection and lane tracking is critical for AV safety, with dynamic object tracking being vital for navigation, as highlighted by Arnold et al. [3] and Nabati et al. [44]. Furthermore, predictive modeling is reinforced by Babaei et al. [6], who stress the importance of forecasting object behaviors for proactive safety. Overall, AI, ML, and sensor fusion are transforming AVs into more intelligent and safer systems capable of adapting to complex driving environments.

Customer-driven requirements: As noted from the findings, the customer-driven requirements often shift during later stages of testing, particularly when edge cases are encountered that challenge predefined functionalities. This aligns with Parekh et al. [46], who emphasize that consumer concerns—especially around safety and reliability—must be addressed for broader acceptance. Furthermore, features such as in-car entertainment (e.g., Netflix or gaming) demonstrate the shift from basic usability to enriched user experiences. However, as AVs become more complex, risk assessment strategies must evolve alongside them, with participants' responses stating that validation tools and testing methods must be redefined as methodologies and tools change. Rosique et al. [50] and Hussain [28] support this by underscoring the importance of ISO 26262 and overall system safety, including protection against mechanical failures.

Region specific adaptation: Regarding the result obtained from region-specific adaptation with broader safety protocols like Euro NCAP has now evolved into finely tuned region-specific homologation standards. This reflects the increasingly fragmented nature of global automotive regulations, demanding flexibility in both design and functionality. The localization of functional requirements—such as sensor resolution and computing capacity—varies not just across continents but often between countries, pushing manufacturers to adapt dynamically. This indicates that regional frameworks significantly influence the AV design pipeline (Babaei et al. [6]; Kuutti et al. [34]). These localization requirements also intersect with vehicle positioning systems that use multiple sensor integrations like LiDAR, IMU, and RTK for precise navigation.

Communication and connectivity: The result obtained from the participants emphasizes the growing importance of communication and connectivity in AVs, particularly as more edge cases surface during testing phases. V2X communication—including Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I)—is a crucial enabler of this interconnected ecosystem, reducing latency and enhancing predictive decision-making. This is echoed in the literature by Yusuf et al.[62], who note that V2X plays a key role in enabling vehicles to share data with surrounding entities. Furthermore, Hussain and Zeadally [28] highlight the advancement of inter-vehicle communication (IVC), which fosters cooperative behavior and real-time crowd sensing, thereby enriching collective perception systems as described by Lobato et al. [39]. Parekh et al. [46] argue that clear communication of system functionality and risks enhances public acceptance.

Real time data processing: The findings about **real time data processing** assure that reaction times are calculated based on speed and stopping distance, highlighting the need for rapid decision-making. This aligns with Babaei et al. [6] and Liu et al.[38], who stress that the perception-to-control cycle must occur within milliseconds to ensure safety. Such performance relies heavily on computational advancements. From the findings in the results session, future improvements like quantum computing could significantly boost processing capabilities. Rosique et al. [50] also emphasize how improved sensors and communication systems enhance vehicle performance. Complex decision-making in ambiguous scenarios, as highlighted by Ayvaz and Cetin [5], further demonstrates that powerful, low-latency computational systems are vital for enabling real-time, safe, and ethical autonomous vehicle behavior.

6.2 (RQ2): What are the most evolving non-functional requirements of autonomous vehicle perception systems development?

Safety: Safety is considered a fundamental requirement in autonomous vehicle (AV) development, underlining the necessity for vehicles to be robust, lasting, and to operate as intended in actual environmental conditions. This perspective aligns with Hussain [28], who describes AV safety as a multidimensional concern centered on preserving human life. Adherence to established safety standards such as ISO 26262 and ISO 21448 ensures system functionality under both critical and non-critical conditions, as discussed by Rosique et al. [50], and echoes the findings of interviewees referring to SORTIF's role in mitigating risks in adverse scenarios. Alongside these safety measures, cybersecurity has emerged as a critical quality requirement. Participants pointed out the vulnerabilities in deep learning models and the growing importance of securing AV systems from manipulation. Babaei et al. [6] reinforce this, highlighting that the perception system cybersecurity is vital, as breaches could cause dangerous behaviors or system failures. Thus, both structural safety standards and robust cybersecurity measures are interdependent pillars supporting the secure deployment of AVs.

Robustness and reliability: are critical for ensuring the consistent performance of autonomous vehicles (AVs) across diverse and unpredictable conditions. As highlighted in the findings, AVs must maintain stable operation in the presence of environmental uncertainties such as poor weather, low visibility, and unclear road markings. This aligns with Kuutti et al. [34], who emphasize that robustness enables AVs to operate reliably despite sensor limitations or adverse surroundings. The findings also reflect the need for AVs to navigate occlusions and unpredictability in traffic behavior, consistent with Hussain et al. [28], who point out that occlusions and uncertain environments can significantly impact prediction accuracy. Moreover, rapid technological advancements in sensors and communication systems have significantly enhanced the performance quality of AVs, as noted by Rosique et al. [50].

User interface (UI): UI is a critical element in autonomous vehicles (AVs), with findings confirming that users expect minimal distraction and intuitive interaction as they shift focus from driving to other activities. This is consistent with Morra et al. [43], who emphasize that effective human-machine interaction (HMI) should provide users with real-time feedback on the vehicle's behavior and environment, thereby enhancing user comfort and confidence. The findings emphasized the crucial role of transparency, especially related to system predictions and data communication, to guarantee that users can comprehend and have faith in the vehicle's decisions. This aligns with Parekh et al. [46], who regard transparency as a non-functional but essential requirement that helps improve user acceptance by making system operations more understandable. Trustworthiness was considered a key factor that strongly connected with cybersecurity and reliability. Literature supports this, with concerns about vulnerabilities in deep learning models and system reliability posing barriers to broader adoption.

Scalability: The findings emphasize that scalability is a critical concern, particularly as sensor integration and cloud-based services continue to expand. The challenge lies not only in processing large volumes of sensory data but also in enabling the system to adapt to dynamic traffic scenarios. This concern is supported by Thandavarayan et al. [54], who highlight the importance of scalable cooperative perception, where vehicles share sensory data to enhance awareness. However, they also point out the risks of system overload and the necessity for efficient communication to prevent congestion on data channels. Additionally, the findings underscore the need for compatibility across hardware, software, and communication modules.

6.3 (RQ3): What are the common challenges of autonomous vehicle perception systems development, and what challenges arise due to the evolving requirements in autonomous vehicle perception systems development?

In the discussion of AV perception challenges, the findings reveal a clear distinction between challenges arising from evolving requirements and those that are more inherent or common. Technological advancement and risk assessment with safety analysis exemplify evolving requirement-driven challenges, as they reflect the need to continuously adapt systems to meet new expectations in functionality, safety, and regulatory standards. In contrast, sensor uncertainty emerges as a common challenge inherent to the physical and environmental limitations of sensing technologies. **Technological advancement:** The findings indicate that the rapid pace of technological advancement is both a driving force and a persistent challenge. As systems evolve, so do the expectations surrounding ADAS features, sensor performance, and software integration, demanding continual innovation to meet these growing requirements. This aligns with Wang et al. [58], who emphasize the necessity of continuous learning and system updates to enhance perception and adapt to novel real-world scenarios. The findings also highlight that increased system complexity has led to a rise in development costs, which is consistent with Hussain and Zeadally [28] who report that software alone can constitute up to 50% of total AV development expenses. Although advancements like Lidar and high-performance compute units are essential, they contribute significantly to production costs, as reflected in the findings.

Sensor uncertainty: The findings reveal that sensor uncertainty significantly influences the reliability and safety of autonomous vehicle (AV) operations, especially in adverse environmental conditions. It was noted that when confidence in sensor data is low, due to weather or sensor failure, critical functionalities such as emergency braking may be disabled to prevent unsafe maneuvers, while noncritical actions like alerts may still be allowed. This aligns with the insights from Babaei et al. [6], who emphasize that perception systems face serious challenges in conditions such as fog, snow, or darkness, which affect sensor accuracy and reduce localization capabilities. The findings also reflect the role of sensor fusion in mitigating these limitations by combining multiple inputs to assess confidence levels, a concept reinforced by Wang et al. [58], who highlight that uncertainties introduced by sensors complicate decision-making, as perception may not always match reality. Additionally, Babaei et al. [6] describe specific sensor drawbacks—such as limited field of view for cameras, LiDAR's sensitivity to certain materials, and radar's difficulty in distinguishing closely spaced objects—all of which contribute to perception uncertainty, as echoed in the findings.

Risk assessment and safety analysis: Participants highlighted the risk assessment and safety analysis through the shared views, if a system fails to meet the required safety thresholds for specific environments, it is restricted from operating in those domains—a concept aligned with the use of Operational Design Domains (ODDs). This perspective is reinforced by Rosique et al. [50], who emphasize the critical consequences of mechanical failures, underscoring the importance of robust systems adapting to varied conditions. The importance of compliance with safety standards such as ISO 26262 was also raised in the findings, which reflects Hussain and Zeadally's [28] assertion that AV validation and testing must meet stringent requirements due to the life-critical nature of these systems. Similarly, the gap between simulation and real-world testing noted in the findings echoes concerns by Parekh et al. [46], who point out that heavy reliance on simulation limits the accuracy of systems like pedestrian detection in real-world contexts. Moreover, participants' concerns around increasing cybersecurity risks are consistent with Babaei et al. [6], who stress that vulnerabilities in perception systems could lead to dangerous interferences or system failures.

6.4 (RQ4): What are the consequences of challenges in the autonomous vehicle perception system development?

Accidents: The findings underscore that accidents in autonomous vehicles often stem from gaps in perception systems, sensor placement, and limitations in detecting blind spots. The findings highlighted that even minor undetected zones, especially in cost-effective models, can result in critical safety failures, highlighting the need for robust hazard analysis and precise sensor integration. These concerns are aligned with the observations of Venugopala [57], who notes that sensor limitations, particularly under adverse environmental conditions, can lead to traffic accidents due to inaccurate environmental perception. Similarly, the challenge of blind spots—strongly emphasized in the findings as an outcome of inadequate sensor configuration and insufficient validation—has been supported by Cui et al. [13], who explain that factors such as occlusion and sensor range constraints can cause dangerous misjudgments. The Tesla Model X incident cited in their study is a stark reminder of these vulnerabilities.

Mechanical or software failures: The findings reveal the fallback mechanisms that ensure safe vehicle behavior in the event of a malfunction, either by returning control to the driver or by safely halting the vehicle. This aligns with Rosique et al. [50], who stress the potentially severe consequences of mechanical or software failures, including accidents and significant human and financial losses. Moreover, the issue of reduced functionality in lower-cost vehicles, as highlighted in the findings, poses additional risks when critical sensors are omitted due to budget constraints. This is supported by Grigorescu [21], who identifies high error rates in current perception systems as a core limitation, preventing AVs from achieving the safety and adaptability of human drivers. Such limitations are especially concerning in vehicles where cost-reduction strategies may lead to compromised safety features. Rosique et al. [50] further emphasize that the cost of such failures extends beyond technical setbacks, affecting consumer trust and slowing the overall acceptance of autonomous technology. Together, these insights underscore the urgent need for redundancy, robustness, and systematic safety design in the electronic and software architecture of autonomous vehicles.

Difficulty in decision-making: The findings illustrate that decision-making remains a particularly complex process, especially when compared to the intuitive and far-sighted judgments humans make in dynamic traffic environments. Ayvaz and Cetin [5] emphasize that decision-making in autonomous systems is not only a technical issue but also an ethical one, particularly in morally ambiguous scenarios where the system must select the “least harmful” outcome. This reinforces the participants’ view that decision-making is far from straightforward in AV contexts. Moreover, Hussain [28] underscores the importance of integrating predictive models with real-time sensor inputs to enable sound decisions, a process that must balance safety, efficiency, and adaptability. Together, these studies support the findings that highlight the limitations of current AV decision-making capabilities and the pressing need for more sophisticated, context-aware models that can rival human judgment under uncertainty.

6.5 (RQ5):How do we mitigate the consequences or challenges of the evolving requirements of autonomous vehicle perception systems development?

Agile methodologies: The findings reveal that agile methodologies are increasingly adopted in the automotive industry, particularly in software-centric development, due to their flexibility in handling evolving requirements and enabling iterative progress. However, their application in hardware systems remains limited because of long planning cycles and regulatory constraints. Scaled frameworks like SAFe help large teams maintain alignment while enabling continuous updates and collaboration, echoed in the findings of Askarpour et.al. [4], which explores agile methodologies in other safety-critical systems also. Agile practices such as backlog-driven workflows, frequent stand-ups, and cross-functional coordination support faster delivery and adaptability. Continuous integration and testing are embedded in workflows to detect early problems and ensure system safety. These findings align with [9], who emphasizes the growing relevance of agile in large automotive teams, the importance of iterative development, and the centrality of testing and feedback. Similarly, [29] highlights agile requirements engineering practices, such as continuous validation and strong user involvement, as essential to delivering high-quality, responsive systems.

Hybrid or mixed methodologies: The findings indicate hybrid or mixed methodologies due to the need for balancing the flexibility of Agile with the structured nature of traditional models. Participants acknowledged the incompatibility of pure Agile with the sequential demands of hardware development, which necessitates structured planning—thereby supporting the use of mixed approaches like Agile combined with Waterfall, SAFe, or the V-model. Berger et al. [9] echoed these findings that pure Agile or traditional models alone are often inadequate in regulated, safety-critical environments like automotive, necessitating tailored hybrid approaches to meet both innovation demands and compliance requirements. and highlighted how elements of the V-model could complement Agile practices. These insights are supported by the findings of Berger et al. [9], emphasizing that the hybrid approach also allows for continuous integration and iterative development, which is essential for software components, while preserving the structure needed for hardware alignment. Kuhrmann et al.[33] support this hybridization trend, noting that European industries widely adopt tailored combinations of Agile and traditional models to accommodate real-world project complexities and regulatory needs.

Free style development: The findings of this study align with the observation of Fitzgerald et al.[17] that large-scale software development is inherently distributed and demands additional coordination practices. As highlighted by a participant's comment referring to a "freestyle" approach, modern development teams are increasingly favoring flexible, adaptive collaboration over rigid structures, even in distributed settings. While traditional coordination tools like JIRA are still utilized, their role is often lightweight, serving as supportive rather than central elements of the workflow. This reflects a shift toward more dynamic, decentralized team practices, emphasizing real-time problem-solving and interpersonal interaction as critical enablers in geographically dispersed environments.

6.6 Validity threats

Validity threats can affect the accuracy and generalizability of research, and addressing biases, contextual factors, and misinterpretations, as noted by McNamara [41], helps ensure more reliable qualitative findings.

6.6.1 Internal validity

The study faces internal validity threats primarily due to the diversity of participant backgrounds and the potential for researcher bias. While the participant pool comprises individuals from various fields related to autonomous vehicle perception systems, including industrial professionals and researchers, their different levels of expertise and professional experiences might lead to variations in responses. These differences could affect the consistency of the collected data, potentially compromising the reliability of the findings. To address this, a manual coding process using Excel and MIRO boards was employed to capture emerging themes and ensure consistency across data interpretation. Furthermore, the thematic analysis involved multiple iterations and cross-checking with supervisors, which helped mitigate bias and ensure a more reliable interpretation of the data.

6.6.2 External validity

A significant external validity arises from the context-specific nature of the development of autonomous vehicles, particularly the variation in rules, regulations, and standards in different countries and regions. These differences can significantly influence how organizations approach technology implementation, testing, and compliance, reducing the findings' generalizability to other geographic or regulatory environments. However, to mitigate this threat, the study was generalizable, and it involved a diverse set of participants, including representatives of multiple companies involved in developing autonomous vehicles, academics, and researchers. This diversity allowed the collection of a wide range of perspectives, generating a more comprehensive understanding of the field. However, the regional and regulatory specificity inherent in the development of autonomous vehicles remains a factor that may influence the applicability of the results to various contexts.

6.6.3 Construct validity

Construct validity in this study was addressed primarily through a rigorous thematic analysis approach, following the six-phase process defined by Braun and Clarke, to ensure that the themes accurately reflect the underlying phenomena under investigation. To maintain consistency in coding and interpretation, we carefully followed each of the 6 phases while identifying and refining themes. A well-structured interview guide, grounded in the research objectives, was developed and tested through pilot interviews to ensure alignment between interview questions and the study constructs. To minimize the risk of misinterpretation inherent in manually coding and analyzing qualitative data, participants were encouraged to ask for clarification during interviews, and the research supervisor reviewed the findings to validate the precision and coherence of emerging themes.

6.7 Future work

To strengthen the current study, future work will aim to expand the scope of participant perspectives by including a more diverse set of stakeholders across different AV development domains, such as regulatory bodies, suppliers, and end-users. This would enhance the generalizability and depth of the findings. Additionally, quantitative validation of the identified challenges and trends through structured surveys or real-world case studies will provide empirical backing to the qualitative insights. Building on the findings and challenges identified throughout this study, several key points for future research in autonomous vehicle (AV) perception systems are proposed. These directions reflect the evolving functional and non-functional requirements, as well as the methodological and regulatory complexities of AV development.

Hybrid development methodologies: The rising adoption of hybrid development methodologies calls for the development of integrated assessment frameworks. Since hybrid supports agile with other methodologies (5.5.2, ID10), future research can explore how Agile and traditional approaches can be systematically evaluated in safety-critical AV contexts, with a focus on aligning software agility with hardware constraints, especially for iterative testing and continuous integration.

Freestyle approach: Furthermore, a deeper understanding is needed of how freestyle approaches scale within larger organizations or cross-functional teams, particularly when coordinating across geographically distributed AV teams. The research gap lies in exploring how tools like JIRA or Confluence can be effectively adapted to support the unique needs of geographically distributed autonomous vehicle teams, particularly in fostering team awareness, communication, and rapid iteration in a freestyle development environment (ID8).

Real-time data processing optimization using advanced computation: As AVs demand ultra-low-latency decision-making, particularly in unpredictable scenarios, exploring computational paradigms such as quantum computing or neuromorphic architectures (ID1) represents a significant research opportunity. Future studies could assess how these technologies overcome current bottlenecks in the perception-to-control cycle. Current research lacks comprehensive studies on applying cutting-edge computing technologies to overcome latency and processing limitations in AV perception, which are critical for real-time decision-making in safety-critical scenarios.

7

Conclusion

This research explored the evolving functional and non-functional requirements of autonomous vehicle (AV) perception systems and the methodologies used to address them. Through qualitative interviews with industry professionals—including Solution Architects, System Designers, and Embedded Software Engineers from leading automotive companies, it became evident that the rapid technological advancement, increased system complexity, and the growing importance of both performance and safety. the AV perception domain is characterized by rapid technological progression, increasing complexity, and a continuous push for innovation. The functional requirements are evolving towards more sophisticated perception capabilities, while non-functional aspects such as scalability, compatibility, safety, and cost-efficiency are becoming equally critical in system development. Key challenges identified include sensor uncertainty, cybersecurity risks, and hardware-software integration issues, which impact safety and decision-making. To navigate these, companies are blending Agile, hybrid, and freestyle development approaches. While Agile fosters adaptability, its limitations in hardware contexts are prompting hybrid solutions like SAFe and the V-model.

There was a difficulty in identifying and recruiting interviewees with expertise across the broad scope of autonomous vehicle perception systems, as many professionals tend to specialize in narrower subdomains within this expansive field. Future research should explore how these mixed methodologies can be systematically evaluated in safety-critical environments, along with the optimization of real-time data processing through advanced computing technologies and better support for geographically distributed teams. Although the findings provide valuable insights for globally representative samples, refined constructs are recommended for future studies to enhance generalizability and depth.

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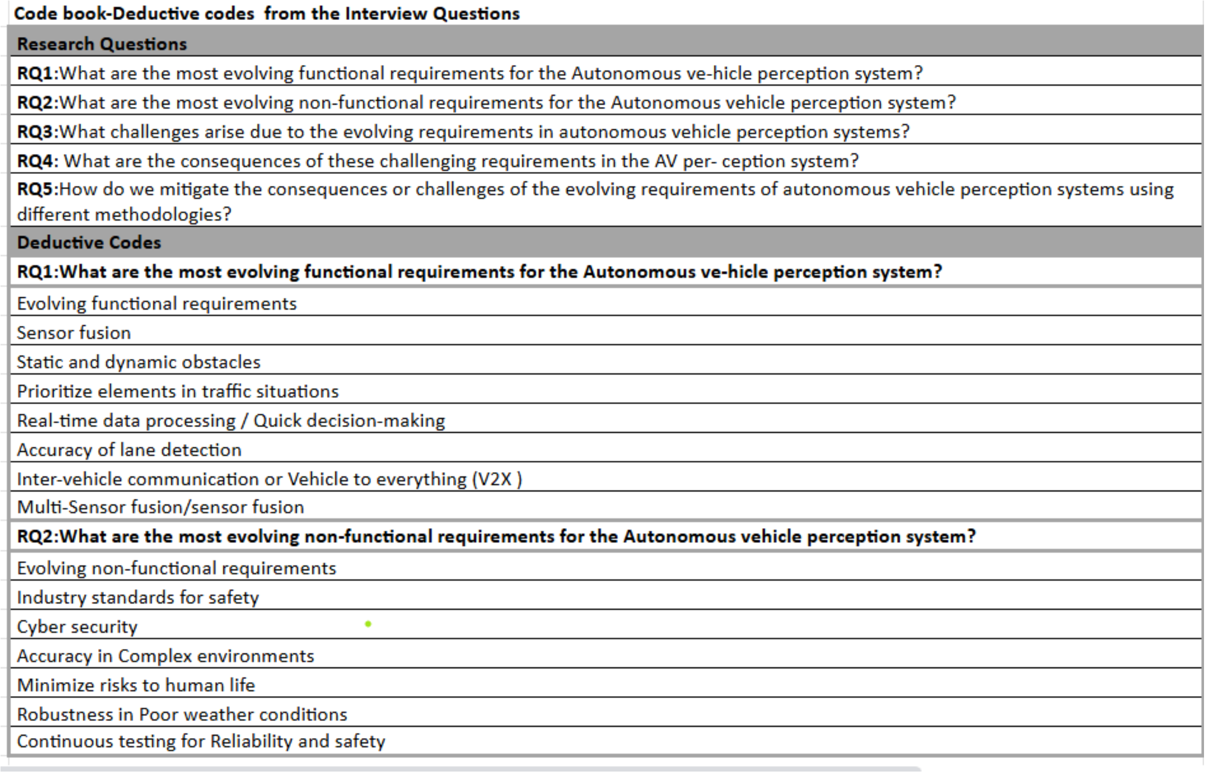
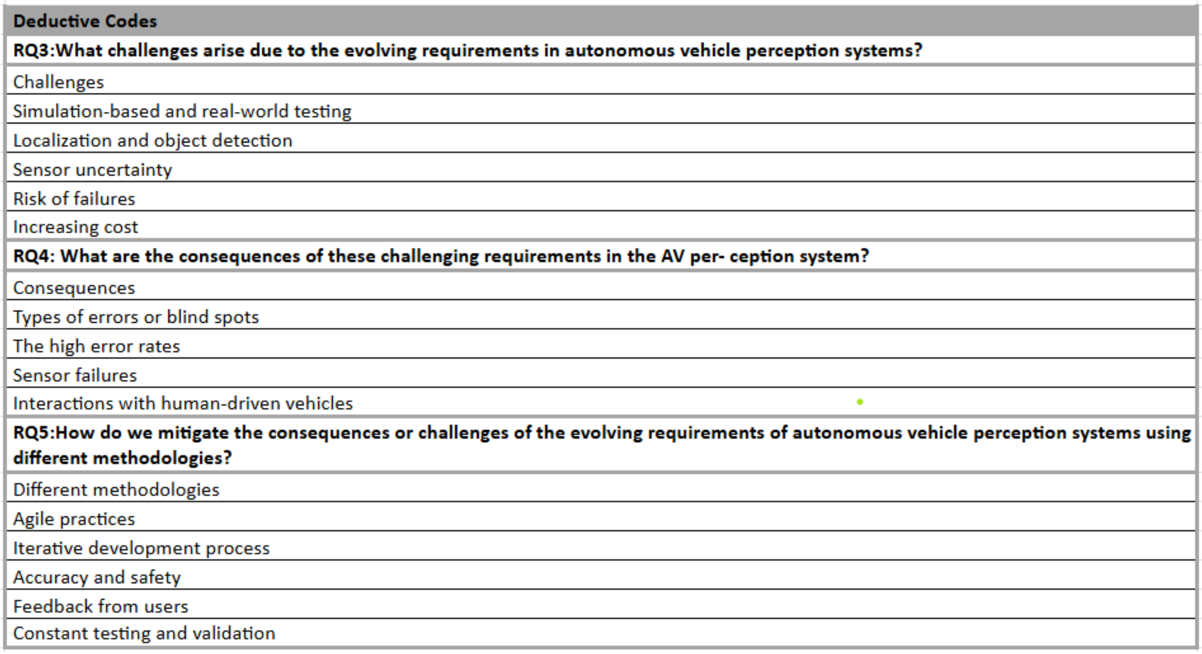
A

Appendix



Code book-Deductive codes from the Interview Questions
Research Questions
RQ1:What are the most evolving functional requirements for the Autonomous ve-hicle perception system?
RQ2:What are the most evolving non-functional requirements for the Autonomous vehicle perception system?
RQ3:What challenges arise due to the evolving requirements in autonomous vehicle perception systems?
RQ4: What are the consequences of these challenging requirements in the AV per- ception system?
RQ5:How do we mitigate the consequences or challenges of the evolving requirements of autonomous vehicle perception systems using different methodologies?
Deductive Codes
RQ1:What are the most evolving functional requirements for the Autonomous ve-hicle perception system?
Evolving functional requirements
Sensor fusion
Static and dynamic obstacles
Prioritize elements in traffic situations
Real-time data processing / Quick decision-making
Accuracy of lane detection
Inter-vehicle communication or Vehicle to everything (V2X)
Multi-Sensor fusion/sensor fusion
RQ2:What are the most evolving non-functional requirements for the Autonomous vehicle perception system?
Evolving non-functional requirements
Industry standards for safety
Cyber security
Accuracy in Complex environments
Minimize risks to human life
Robustness in Poor weather conditions
Continuous testing for Reliability and safety

Figure A.1: Codebook



Deductive Codes
RQ3:What challenges arise due to the evolving requirements in autonomous vehicle perception systems?
Challenges
Simulation-based and real-world testing
Localization and object detection
Sensor uncertainty
Risk of failures
Increasing cost
RQ4: What are the consequences of these challenging requirements in the AV per- ception system?
Consequences
Types of errors or blind spots
The high error rates
Sensor failures
Interactions with human-driven vehicles
RQ5:How do we mitigate the consequences or challenges of the evolving requirements of autonomous vehicle perception systems using different methodologies?
Different methodologies
Agile practices
Iterative development process
Accuracy and safety
Feedback from users
Constant testing and validation

Figure A.2: Codebook