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Guidelines for reducing perception errors in Autonomous Vehicle System Architecture

By

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Guidelines for reducing perception errors in Autonomous Vehicle System Architecture

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Abstract

Autonomous vehicles (AVs) are poised to reshape the future of transportation, and the autonomous driving system impacts the overall safety of the driving system. Effective operation of AVs requires a vast deployment of sensor technologies for environmental perception and to acquire information on road conditions. While reliable perception is crucial for the success of AVs, perception errors represent a critical technical challenge in Avs. They can result in incorrect decision-making and unsafe driving behaviours. These perception errors significantly compromise vehicle safety and impede the successful commercialisation of autonomous driving systems.

This study employed the Design Science Research Methodology (DSRM) process to develop a set of guidelines to minimise the perception errors of AVs, leading to a safer and more reliable autonomous driving experience. The development of these guidelines was a consequence of the triangulation of extant literature, internal validation and empirical data gathered through expert reviews using an online questionnaire. The study followed an embedded mixed-methods approach. A wide group of experts was drawn from the automotive industry in South Africa, the United States of America (USA), Hungary, and the United Kingdom (UK). Some of the experts were sourced through a reputable online platform, Prolific. The descriptive data analysis method was employed to analyse and interpret the data.

Seven perception layer tasks discovered from the literature were presented to experts during the evaluation process. The results validated the importance of the seven perception layer tasks (viz., Object Detection and Classification, Lane Detection and Tracking, Real-Time Feedback, Assess Potential Obstacles, Sensor Data Fusion, Dynamic Adaptation, Localisation), and four additional tasks emerged from the evaluation process (viz., Motion Forecasting, Safety System Integration, Free Space Detection, and Weather Condition Detection and Response). The main contribution of this study is a set of guidelines, deemed potentially effective for mitigating perception errors in AVs. Importantly, the results validated the relevance of the preliminary guidelines, improved the quality of their design and underscored the need for further investigation into the implementation of their requirements.

KEYWORDS: Autonomous Vehicle, Autonomous Vehicle System Architecture, Design Science Research, Perception Errors, Guidelines, Automotive Industry

Declaration

I, Itumeleng Ramala, hereby declare that:

The work contained in this thesis, titled Guidelines for reducing perception errors in Autonomous Vehicle System Architecture, submitted in fulfilment of the degree of Master of Commerce in Information Systems at Rhodes University, is my work, and no prior submissions have been made. All sources consulted or cited have been documented and acknowledged. The researcher is fully aware of Rhodes University's policy on plagiarism and has undertaken all necessary efforts to adhere to the established regulations.

Itumeleng Ramala Ramala.
Name Surname (signed)

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"*Ideas don't come out fully formed, they only become clearer as you work on them. You just have to get started*" - Mark Zuckerberg

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List of Abbreviations

Abbreviation	Description
ADAS	Advanced Driver Assistance Systems
AI	Artificial Intelligence
AV	Autonomous Vehicle
AVSA	Autonomous Vehicle System Architecture
CV	Connected Vehicle
DSR	Design Science Research
DSRM	Design Science Research Methodology
FEDS	Framework for Evaluation in Design Science Re-search
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
ICT	Information and Communication Technology
IS	Information Systems
ISO	International Organization for Standardization
LiDAR	Light Detection and Ranging
NHTSA	National Highway Traffic Safety Administration
PAS	Publicly Available Specification
RADAR	Radio Detection and Ranging
SA	South Africa
SAE	Society of Automotive Engineers
SLAM	Simultaneous Localisation and Mapping
UK	Unite Kingdom
USA	United States of America
V2C	Vehicle-to-Cloud
V2I	Vehicle-to-Infrastructure
V2N	Vehicle-to-Network
V2P	Vehicle-to-Person
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything

Chapter 1: Introduction

1.1 Research Background

Research in autonomous driving has gained momentum due to the inherent advantages of autonomous driving (Bachute and Subhedar, 2021). The present-day automotive industry is concerned with much more than the traditional view of assembled mechanical parts controlled by humans for transportation (Pelliccione et al., 2017). It is transforming towards innovative, connected, autonomous, and electric vehicles that offer contextual, intelligent, and personalised customer experience (Karmanska, 2021). The autonomous vehicles (AVs) concept is a developing concept in transportation (Kumar et al., 2022). AVs are cars that move between points, fulfilling the operations of traditional cars without human intervention. It combines sensors and software to control, navigate, and drive the vehicle (Rosique et al., 2019). However, AVs are significantly influenced by connected vehicles (CVs) (Rana and Hossain, 2023). CVs can be defined as cars that combine ICT and automobiles, enabling them to connect and communicate with other cars, the external network, and devices within themselves (Karmanska, 2021; Ahmed et al., 2022; Rana and Hossain, 2023).

Connected and Autonomous Vehicles have reshaped the automotive industry and how transportation is perceived (Vdovic, Babic and Podobnik, 2019; Abdelkader, Elgazzar and Khamis, 2021; Karmanska, 2021; Lu and Shi, 2022). The introduction of AVs includes a vast deployment of sensor technologies within modern vehicles that aid in designing and developing various applications for traffic management safety (Abdelkader, Elgazzar and Khamis, 2021). AVs reduce human intervention and rely on sensors and systems to conduct driving tasks, depending on the level of automation (Rana and Hossain, 2023).

The automation levels of the vehicles depend on the complexity of the autonomous technology applied and the perception range of the environment they drive in. They are further determined by the degree to which a human driver or vehicle system gets involved in the driving decision. These factors are closely linked to the overall safety of AVs (Wang et al., 2020). The traditional definition of automation levels consists of ten levels and was defined in 1987 by Sheridan and Verplank (Endsley, 2018; Wang et al., 2020) and later modified in 2000 by Parasuraman, Sheridan, and Wickens (Wang et al., 2020). However, this study uses the definition of automated levels published by the Society of Automotive Engineers (SAE), which is updated regularly. The definition of automated levels by SAE includes six automation levels (viz. Level 0 – No Automation, Level 1 – Driver Assistance, Level 2 – Partial Driving Automation, Level 3 – Conditional Driving Automation, Level 4 – High Driving Automation, Level 5 – Fully Driving Automation) (Ionita, 2017; Ondruš et al., 2020; Wang et al., 2020; Karmanska, 2021; Ahmed et al., 2022; Rana and Hossain, 2023).

Level 2 (i.e., Partial Driving Automation) is the focus of this study as it is the current base-level of operation for most AVs (Wang et al., 2020; Karmanska, 2021). However, there are related challenges presented by Kumar et al. (2022) which include economic, market penetration, technical, infrastructure, legal and policy, and safety challenges. A key consideration in this study is the critical challenge of safety in the development and operation of AVs (Wang et al., 2020). A causal relationship exists between safety and technical challenges, in that safety is mainly precipitated by the technical challenges experienced in relation to successfully commercialising AVs (Wang et al., 2020). Therefore, this study focused on the technical challenges. These are the most difficult challenges that AV innovation must overcome (Kumar et al., 2022). The three key technical challenges can be classified as perception, decision, and action errors (Wang et al., 2020; Kumar et al., 2022).

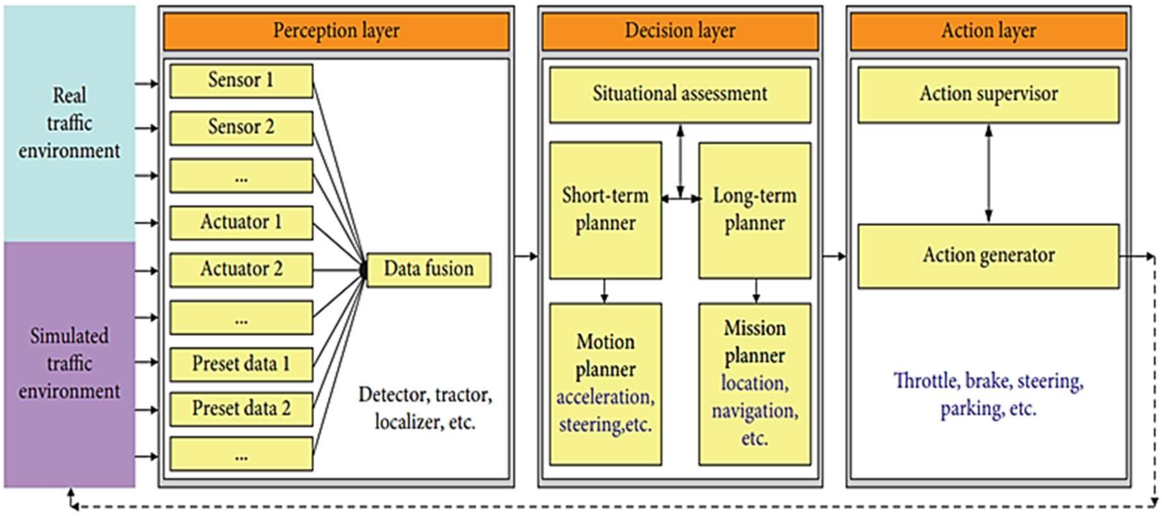

Figure 1.1: AV system architecture (adapted from Wang et al., 2020)

The Autonomous Vehicle System Architecture (AVSA), depicted in Figure 1.1, comprises a sensor-based perception layer, an algorithm-based decision layer, and an actuator-based action layer. The errors (i.e., perception, decision, and action errors) occur at each of these layers, respectively. These errors are as follows:

- **Perception Errors:**

  The perception layer collects data from multiple sensor devices to perceive environmental conditions for real-time decision-making (Wang et al., 2020). This layer fuses the collected data to generate the relevant information required by the decision layer (Wang et al., 2020). Sensors for environment perception include light detection and ranging sensors (LiDAR), cameras, radio detection and ranging sensors (RADARs), ultrasonic sensors, contact sensors, and global positioning systems (GPS) (Wang et al., 2020). A safe AV should be able to obey traffic laws and avoid road hazards automatically and effectively. However, any errors in the perception of other road users' status, location, movement, traffic signals, and other hazards may raise safety concerns (Wang et al., 2020). It has proven to be challenging to accurately localise, categorise, and detect objects in the environment to mitigate perception errors (Storck and Duarte-Figueiredo, 2019; Wang et al., 2020).

- **Decision Errors:**

  The decision layer evaluates and interprets the processed data from the perception layer to make decisions and generate relevant information required by the action layer for route planning and mission planning, or making quick decisions to avoid obstacles and generating trajectories (Wang et al., 2020; Kumar et al., 2022). Decision errors arise when inaccurate information has been transmitted from the perception layer, leading to an incorrect analysis of the environment.

- **Action Errors:**

  The action layer acts on the commands from the decision layer (Wang et al., 2020; Kumar et al., 2022). Some of the actions taken by the action layer are the control of the steering wheel, throttle, or brake to change the direction, accelerate, or decelerate (Wang et al., 2020). Similar to the decision layer, some action errors arise due to the faults of the perception layer and incorrect decisions from the decision layer.

The failure of the perception layer may mislead the decision and action layers. In instances where perception errors may not be resolved, they may cause the vehicle to either fail the mission or cause safety problems (Wang et al., 2020). Therefore, it is essential to determine how vehicles efficiently understand the environment and take correct actions in real-time. This process starts at the perception layer of the AVSA, providing the system data for decision-making from the external environment (Liu et al., 2020; Wang et al., 2020; Kumar et al., 2022).

1.2 Research Problem

Considering the research context, the research problem of this study is predicated on the reliability of the perception capabilities and improved safety of AVs. The perception layer heavily relies on sensing technology; and the complexity, reliability, suitability, and maturity of sensing technology determine the development of AVs (Wang et al., 2020; Ahmed et al., 2022; Kumar et al., 2022). Reliable perception is crucial for the success of AVs, and perception errors pose a significant challenge, leading to inaccurate decisions and unsafe driving actions, ultimately impacting mission outcomes and causing safety issues (Liu et al., 2020; Wang et al., 2020).

The leading cause of AV fatalities in 2018 was determined to be perception errors (Piazzoni et al., 2023). The underdeveloped state of environmental perception technology remains the main obstacle to enhancing the overall performance of AVs and hindering their wide-scale commercialisation (Wang et al., 2020). Liu et al. (2020) noted that four of five AV fatalities between 2016 and 2019 involved Tesla cars, with one involving Uber. All four Tesla fatalities were due to perception failures. The perception errors for the Tesla fatalities ranged from perception failures, such as mistaking a truck for open sky, to failing to recognise highway dividers or semi-trailers. Uber incidents in 2018 were attributed to difficulties predicting human behaviour. All the incidents that occurred were due to the incorrect detection of objects and the inability to predict their behaviour. These highly publicised AV accidents have raised concerns about the safety and reliability of the technology (Katiyar, Shukla and Chawla, 2024). AVs need to be able to detect and predict the trajectories of other objects in the environment to reduce perception errors (Su, 2023). Apart from driving at high speeds, most AV accidents occur due to traffic signals and sign violations. This shows that continuous research and testing are crucial to improving AV perception capabilities (Ramanagopal et al., 2018; Szűcs and Hézer, 2022; Katiyar, Shukla and Chawla, 2024).

1.3 Research Questions

The main research question that this study seeks to answer is:

How can perception errors be reduced in Autonomous Vehicle System Architecture to improve safety and limit technical challenges?

The research sub-questions considered are:

RSQ1: What should be the key tasks of the perception layer of the Autonomous Vehicles System Architecture?

RSQ2: What are the technical enablers and challenges encountered in autonomous vehicles?

RSQ3: What guidelines could be followed to reduce perception errors in the Autonomous Vehicle System Architecture?

1.4 Research Aim and Objectives

The aim of this study is to develop a set of guidelines to minimise the perception errors of AVs, leading to a safer and more reliable autonomous driving experience. These guidelines are further intended to add to the body of knowledge in relation to the AV system architecture.

This will be developed using the following research objectives:

- Determine the main tasks of the perception layer of the Autonomous Vehicles System Architecture.
- Provide an analysis of technical enablers and challenges that are encountered in AVs.
- The final deliverable of this study is a set of guidelines to minimise the perception errors of AVs, leading to a safer and more reliable autonomous driving experience.

1.5 Research Design and Methodology

This study seeks to guide practitioners and developers on how to reduce perception errors in AVs, particularly at the perception layer of the AV. It has been argued that IS research primarily uses positivism, interpretivism, and critical paradigms (Saunders, Lewis, and Thornhill, 2016). However, this study subscribes to the pragmatism research philosophy as it seeks to contribute an innovative artefact as guidelines to solve a real-life problem (Hevner and Chatterjee, 2010; vom Brocke, Hevner and Maedche, 2020). This study contributes a practical solution that informs future practice (Saunders, Lewis and Thornhill, 2019). The study employs the Design Science Research (DSR) as the theoretical lens to develop a set of guidelines. DSR follows an incremental approach, emphasising the constant refinement of an artefact from its initial conceptual stage to a final output design as informed by multiple contributions (Peffers et al., 2007). To fulfil the DSR requirements, the seminal Design Science Research Methodology (DSRM) defined by Peffers et al. (2007) guided this study, and it was conducted using a two-phased approach. The DSRM process, which guided the development of this study, is applied as depicted in Figure 1.2 below and further discussed in Chapter 2.

This study followed an embedded mixed-method approach, collecting both quantitative and qualitative data to improve the guidelines accordingly. Furthermore, the approach to theory development deemed appropriate for this study was the abductive reasoning approach, which combines inductive and deductive reasoning (Saunders, Lewis and Thornhill, 2019). The initial set of guidelines derived from the literature was presented to experts within the automotive industry to evaluate and critique the guidelines. This was achieved through an online questionnaire with a limited number of experts through purposive sampling (Hevner and Chatterjee, 2010).

The research questions focused and guided the scope of exploration and the direction taken (Bell, Bryman, and Harley, 2018). Purposive sampling is frequently utilised when working with relatively small samples, such as in case study research (Saunders, Lewis and Thornhill, 2019). A case study research strategy was deemed appropriate for this study, using South Africa as the ideal unit of analysis. A case study technique provided insights through an intensive and in-depth investigation into the study of phenomena in its real-world setting, resulting in detailed, empirical descriptions and the development of the theory (Saunders, Lewis and Thornhill, 2019).

The experts' evaluation results were analysed descriptively to provide insights to refine the final set of guidelines.

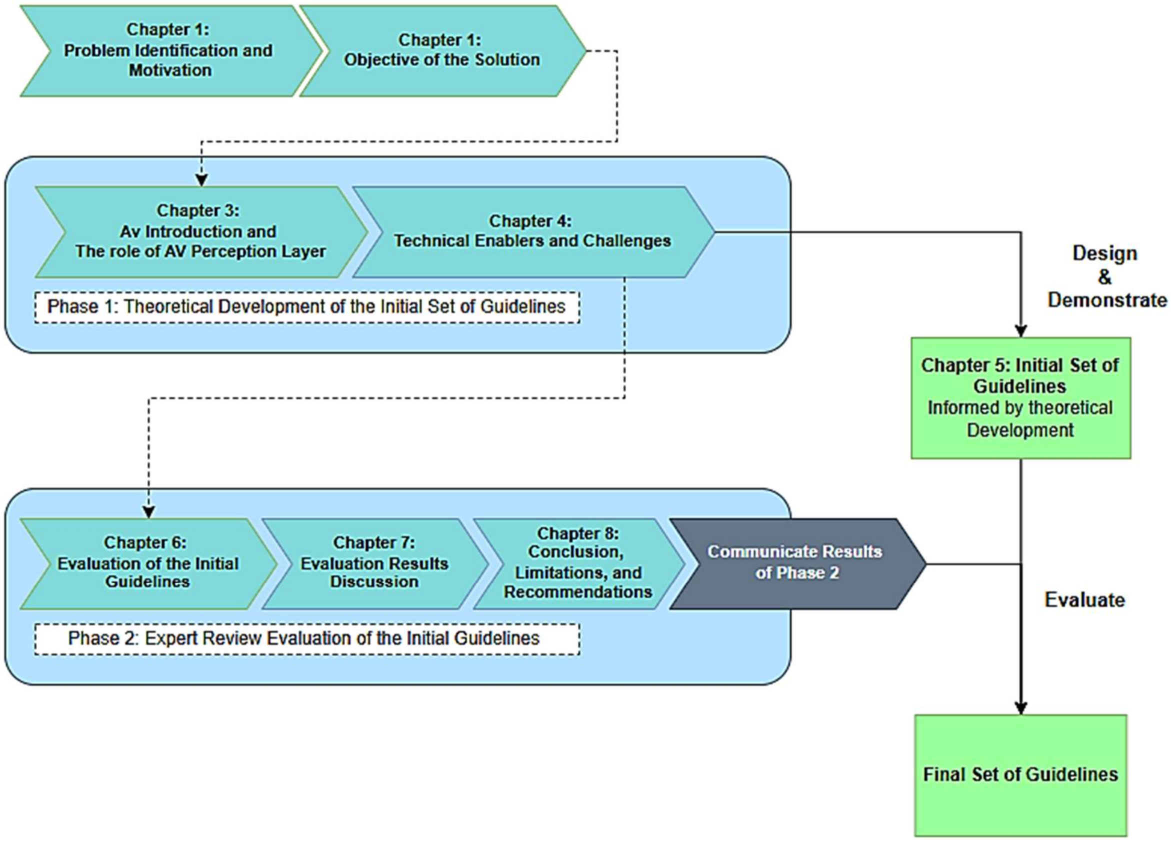

Figure 1.2: DSRM application process (adapted from Peffers et al., 2007; Myllyoja et al., 2016)

1.6 Ethical Consideration

This study included human participants; therefore, ethical permission from the Rhodes University Human Ethics Committee (RU-HEC) was necessary. Participation in this study was entirely voluntary. The gatekeeper from Company 1, a global motor vehicle manufacturer based in the Eastern Cape, declined our request to collect data from their company, citing the risk of potential disclosure of confidential company information and employee demotivation. Conversely, the gatekeeper's permission from the Head of Corporate Strategy at Company 2 was received. Company 2 is also a global brand which is based in the Eastern Cape. Furthermore, in order to advance the study, it became necessary to use a reputable online platform, Prolific, to collect data. The use of Prolific did not require gatekeeper permission, as the researcher approached the professionals in Prolific database in their professional capacity, not based on their company affiliations.

1.7 Research Outline

The research chapters are in sequential order:

- Chapter 1: Lays the foundation and goals of this study by introducing the research background, problem, questions, and objectives.
- Chapter 2: This chapter outlines the research methodology used to develop this study and discusses how the DSRM process was applied.
- Chapter 3: Informed by RSQ1, this chapter defines AVs and the main tasks of the perception layer. It is crucial to define the tasks of this layer to understand and position the Guidelines appropriately.
- Chapter 4: This chapter is guided by RSQ2 to explore the technical enablers and challenges associated with AVs as presented in prior literature. This chapter also contributes to the theoretical foundations of the intended guidelines as the output of this study. The chapter further defines requirements that have the potential to add value to the initial guidelines.
- Chapter 5: Guided by the RSQ 3 and the key themes drawn from chapters 3 and 4, this chapter introduces the initial set of guidelines and establishes the correlation between the perception layer tasks, challenges and key enablers discussed in prior chapters.
- Chapter 6: The chapter focuses on the evaluation of the initial guidelines. The evaluation strategy and the results from the expert reviews are presented.
- Chapter 7: This chapter provides the discussion of the perception tasks and guidelines results from Chapter 6 and subsequently provides the final set of guidelines and the final perception tasks.
- Chapter 8: The chapter reflects on the research process undertaken, outlining the researcher's key learning areas, and includes recommendations for future studies to conclude the investigation.

Chapter 2: Research Methodology

2.1 Introduction

Research methodology refers to the research design, methods, approaches, and inquiry procedures used to solve a research problem (Kamau, 2022). This chapter introduces the research paradigm that guided this study. It further discusses the Design Science Research Methodology (DSRM) process that guided the development of the final set of guidelines. Additionally, data collection and sampling techniques are provided and discussed.

2.2 Research Paradigm

A research paradigm is a fundamental worldview that serves as the foundation for a research investigation. Further, it is a conceptual lens through which the researcher examines the methodological aspects of their research project to determine the research methods that will be employed and how the data will be analysed (Kivunja and Kuyini, 2017).

The most often used paradigms in Information Systems (IS) research are positivism, interpretivism, and critical realism (da Silva et al., 2018; Saunders, Lewis and Thornhill, 2019. However, the preferred paradigm for this study is pragmatism. The positivist and interpretivist paradigms have been criticised for their extreme positions on research methods and approaches, reinforcing the need for a pragmatic philosophical stance in IS research (Alharahsheh and Pius, 2019; Kamau, 2022). For example, the positivist paradigm is noted for advancing the concept of objectivity towards confirmation and falsification while neglecting the reality that numerous human decisions are made throughout the research process. In contrast, the interpretivism paradigm proposes that a phenomenon must be interpreted according to the subjective knowledge of human experiences and actions.

Pragmatism facilitates various ways of interpreting the world and conducting research. It is based on the notion that no single point of view can provide the entire picture and that different realities may exist (Saunders, Lewis and Thornhill, 2019). The pragmatic paradigm denotes that it is impossible to access the truth about the real world exclusively through a single scientific method, as proposed by the positivist paradigm, and that it is impossible to determine social reality as defined by the interpretivism paradigm (Kamau, 2022). Pragmatists employ methods that allow for the collection of credible, well-founded, reliable, and relevant data to advance a study (Saunders, Lewis and Thornhill, 2019). Similarly, in this study, the researcher initially planned to gather data from South African industry experts. However, this was met with challenges as explained in section 2.10, where some companies were reluctant to share data. Consequently, the researcher had to adapt the approach in real-time and undertook a pragmatic approach to collect data from the online platform of professionals, Prolific. This resulted in the collection of critical data that helped to refine the initial set of guidelines as an artefact of this study.

Pragmatism is a school of thought that considers practical consequences. It asserts that action and practical relevance should be the focal areas of scientific inquiry (Goldkuhl, 2012; da Silva et al., 2018). It is premised on the assertion that truth and utility are two sides of the same coin, and that scientific research should be evaluated considering its practical implications (Goldkuhl, 2012). This guided the study to ensure that the guidelines are evaluated in a real-world setting by experts (truth) to verify their applicability and relevance in the autonomous vehicles (AV) context (utility).

The assumptions that underpin the pragmatic paradigm influenced how the researcher formulated the research questions, the methods used, and how the findings were interpreted (Saunders, Lewis and Thornhill, 2019; Chege and Otieno, 2020; Muhaise et al., 2020). These assumptions relate to ontology, epistemology, axiology and the research methods that have been preferred in this study (as shown in Table 2.1 below)

Table 2.1: Pragmatism philosophy research assumptions (adapted from Saunders, Lewis and Thornhill (2019); Muhaise et al. (2020); Kamau (2022))

Ontology *(nature of reality or being)*	**Epistemology** *(what constitutes acceptable knowledge and who can know)*	**Axiology** *(what is the role of values)*	**Research methods**

- Complex, rich, external - “Reality” is the practical consequences of ideas - Flux of processes, experiences, and practices	- Practical meaning of knowledge in specific contexts - ‘True’ theories and knowledge are those that enable successful action - Focus on problems, practices, and relevance - Problem-solving and informed future practice as a contribution	- Value-laden research - Research initiated and sustained by the researcher’s doubts and beliefs - Researcher reflexive - Multiple stances: researchers include both biased and unbiased perspectives	- Following the research problem and research question - Range of methods: mixed, multiple, qualitative, quantitative, action research - Emphasis on practical solutions and outcomes

This study is positioned within pragmatism based on these assumptions because they underscore the objective of this study, which is to develop guidelines that will help guide practitioners and researchers on how to minimise perception errors in AV to improve safety, user driving experience, and create a better environment.

Pragmatism also advocates that the practical relevance of the study results should be considered equally as high as the rigour of the research undertaken to achieve the conclusion (Aparicio, Aparicio and Costa, 2023). Further, pragmatism is concerned with action and change and with the interaction between knowledge and action. da Silva et al. (2018) note that pragmatism is the most appropriate paradigm in cases where intervention is an organisational change or the construction of artefacts, as contemplated in this study. The objective of this study is to offer an innovative artefact in the form of guidelines to address a real-life problem (Hevner and Chatterjee, 2010; vom Brocke, Hevner and Maedche, 2020).

This study considers pragmatism as the underpinning philosophy for Design Science Research (DSR), which is the preferred approach for this study, as discussed in section 2.5

(Goldkuhl, 2012; van der Merwe, Gerber and Smuts, 2020). The pragmatist perspective is fit for DSR based on the focus on utility and knowledge growth through development, starting with a problematic situation and aiming for knowledge building (van der Merwe, Gerber and Smuts, 2020).

Pragmatism's decision-making does not restrict its methodological choices (da Silva et al., 2018). It focuses on effective methods to meet specific criteria and allows researchers the flexibility to choose from various approaches when addressing the research question (Kamau, 2022). A mixed-methods approach was selected for this study, as outlined in section 2.4.

2.3 Reasoning Approach for Theory Development

In alignment with the pragmatism research paradigm, the abduction reasoning approach to theory development is preferred in this study over the induction and deduction reasoning approaches. As shown in Figure 2.1, abduction represents the synthesis of deduction and induction, where the intention is to create a context of meaning by essentially integrating hypotheses, theories, or explanations and precedes deductive and inductive reasoning approaches (Karlsen, Hillestad and Dysvik, 2021). Induction means the process of reasoning from specific empirical observations to more general rules. Deduction is the process of developing specific predictions from general principles (Karlsen, Hillestad and Dysvik, 2021; Okoli, 2021).

Appendix A shows the difference between deduction, induction and abduction reasoning approaches.

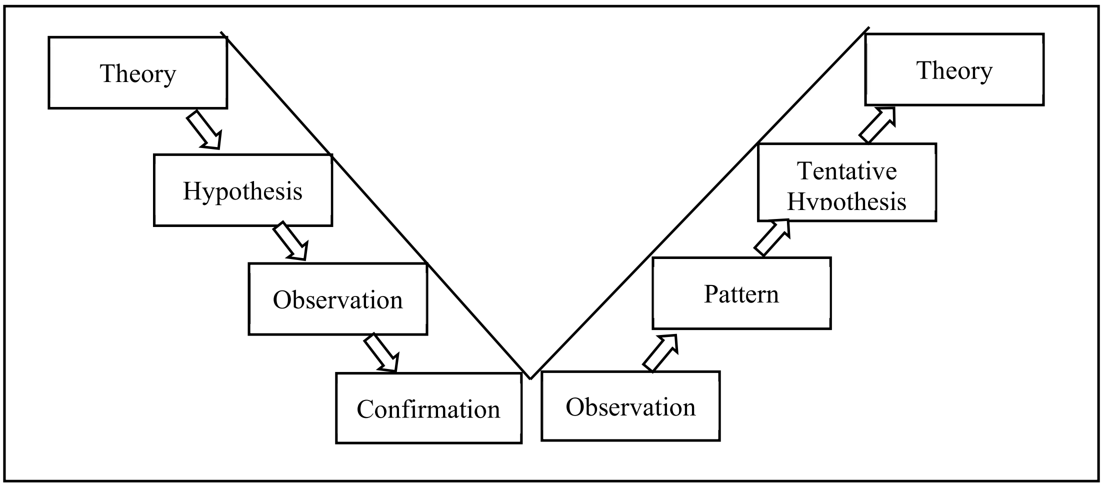

Figure 2.1: Deductive and inductive reasoning approaches (adapted from Aliyu et al., 2015)

The abductive reasoning approach was applied in this study in the following manner: data collected during the literature review informed the development of the preliminary guidelines –

inductive process. The research design and instrument used to empirically evaluate the preliminary guidelines through an online questionnaire and expert evaluations to make inputs into the finalised guidelines – a deductive process.

2.4 Methodological Choice

This study followed a mixed-methods approach. A mixed-methods approach is the combination of qualitative and quantitative methods in the same study (Molina-Azorin, 2016). The combination of qualitative and quantitative methods offers a better understanding of the research problem than either approach by itself (Clark et al., 2008; Ahmed, Pereira and Jane, 2024). There are four mixed methods designs: triangulation/concurrent, explanatory, exploratory, and embedded designs. The study follows the embedded mixed-methods design. In an embedded design, similar to this study, the researcher uses one type of data in a supportive role to the other method type (Clark et al., 2008; Saunders, Lewis and Thornhill, 2019). This study collected both qualitative and quantitative data to ensure sufficient triangulation with the literature review.

2.5 Design Science Research (DSR)

This study adopted Design Science Research (DSR) as a theoretical lens. DSR is a recognised and acceptable research methodology in the field of IS (Akoka et al., 2023; Brunner et al., 2023). DSR is best suited for this study as it provides practical solutions in a complex context (Iyawa, Herselman and Botha, 2019). DSR is a problem-solving approach that seeks to enhance human knowledge via the creation of innovative artefacts (vom Brocke, Hevner and Maedche, 2020; Brunner et al., 2023). DSR focuses on creating and evaluating IT artefacts intended to solve identified organisational problems (Iyawa, Herselman and Botha, 2019; Aparicio, Aparicio and Costa, 2023).

This study adopts DSR to develop a set of guidelines, which serve as the artefact of this study. The guidelines are offered as a practical solution intended to be applied by AV developers and engineers during the design and development of AVs. The primary aim of the proposed guidelines is to minimise perception errors in AVs, leading to a safer autonomous driving experience. As noted by vom Brocke, Hevner and Maedche (2020), DSR seeks to enhance the technology and science knowledge base by creating innovative artefacts that solve problems and improve the environment in which they are instantiated.

Figure 2.2 below presents a conceptual framework for understanding, executing, and evaluating design science research.

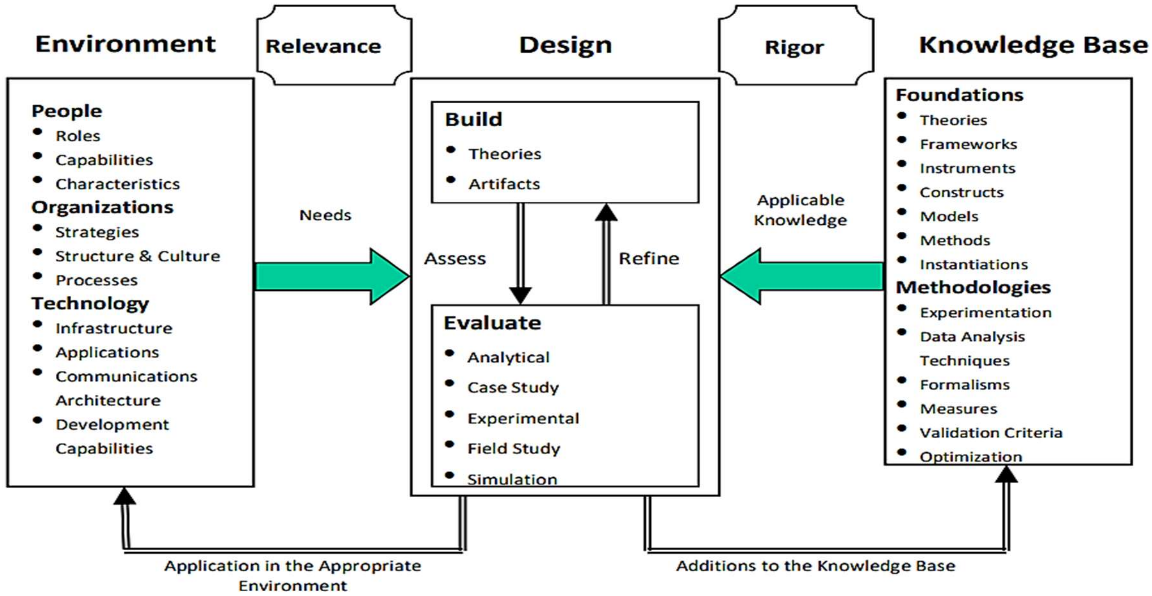

Figure 2.2: Design Science Research Framework (adapted from Hevner et al., (2004).

The framework is made up of three main pillars:

- The first pillar is the environment. It defines the problem space in which the phenomena of interest reside. This environment is composed of people, organisations, and existing or planned technologies. Needs are assessed and evaluated within the context of organisational strategies, structure, culture, and existing work processes. The needs are positioned relative to existing technology infrastructure, applications, communication architectures, and development capabilities. The relevance of this study lies in structuring the research activities to address real stakeholder needs. Together, the environment and needs define the research problem. Therefore, this pillar was applied in Chapter 1 of this study (sections 1.1 & 1.2), where the environment and needs are discussed.
- The second pillar is the knowledge base. It provides the raw materials through which DSR is accomplished. Prior research and results from reference disciplines provide foundational theories, frameworks, instruments, constructs, models, methods, and instantiations used in the build phase of a research study. Methodologies provide guidelines used in the evaluation phase of the DSRM process. Rigour is achieved by appropriately applying existing foundations and methodologies. The better the needs are understood, the better the existing knowledge can be applied, and the better the artefact can be shaped and evaluated (Brunner

et al., 2023). In this study, extant literature was used as the foundational applied knowledge to address the research sub-questions outlined in section 1.3, thereby ultimately addressing the needs of this study. The reviewed literature is presented across Chapters 3 to 5, guided by the research sub-questions (see section 1.3). This applied knowledge additionally informed the methodologies that underpinned this study. The rigorous literature review process was instrumental in ensuring that the proposed guidelines were firmly developed and rooted in existing knowledge.

- The last pillar is the design and contains the development of the guidelines, which is based on the needs of the automotive environment and applicable knowledge from the knowledge base. The core principle of DSR is the evaluation and the constant cycle of evaluating, refining and evaluating the guidelines. In this study, applied knowledge drawn from the knowledge base was critical to build, assess, evaluate, and refine the proposed guidelines, thereby shaping and enhancing their utility. The extant literature informed the design and development of the initial set of guidelines, presented in Chapter 5. To assess the relevance of these guidelines, experts evaluated them using an online questionnaire (as detailed in section 2.9). The subsequent results, presented in Chapter 6, facilitated the refinement of the initial set of guidelines, leading to the development of the final set of guidelines.

As illustrated by the framework, DSR contributes both to the environment in the form of guidelines with practical value and to rigour in the form of new knowledge (van der Merwe, Gerber and Smuts, 2020).

2.5.1 Four-Cycle View of DSR

The foundation of DSR has been demonstrated through a widely recognised Three-Cycle model presented by Hevner (2007). The Three-Cycle model DSR extends the Design Science Research Framework (see Figure 2.2 above) by overlaying it with a focus on three inherent research cycles – relevance, rigour, and design. However, due to the dynamic nature and complexities of various environments, the three-cycle model has been further extended to incorporate and adapt to expected changes through the change and impact cycle (Drechsler and Hevner, 2016), as shown in Figure 2.3 below.

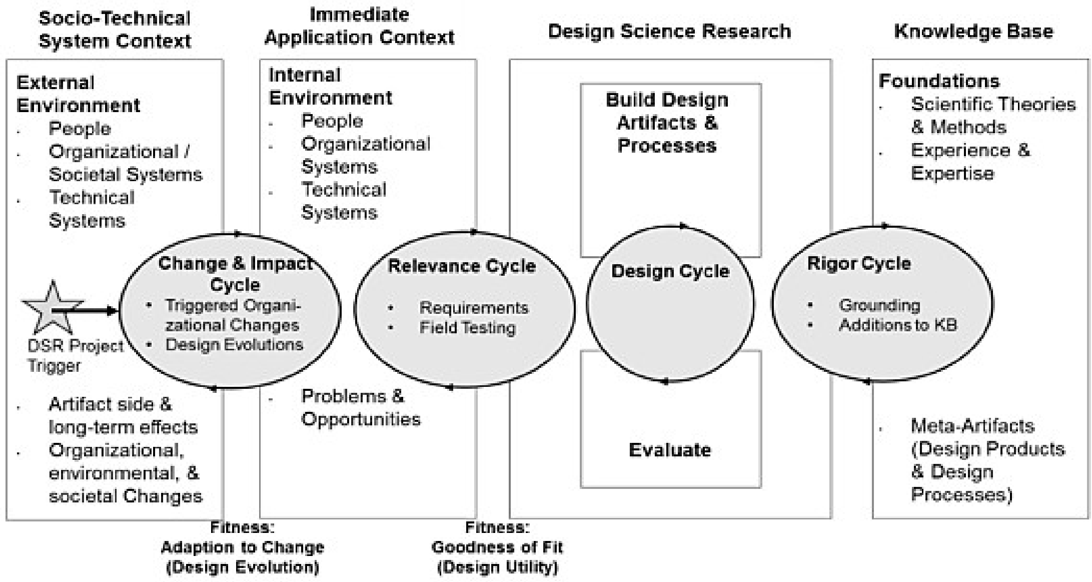

Figure 2.3: DSR Four-Cycle View (adapted from Drechsler and Hevner, 2016)

The following sections describe each of the cycles and their relevance to this study in the development of the initial guidelines (Hevner, 2007; Drechsler and Hevner, 2016):

a) **Change and Impact Cycle**

Considering the pervasive and dynamic nature of IS research, the design process considers probable advancements through the Change and Impact Cycle. Through this cycle, the need to create adaptable artefacts was evaluated to ensure that the relevance of the designed output remains intact. This study identified that the comprehensive safety solutions to improve the perception layer were still missing. Furthermore, the study contributes towards closing this gap by producing a set of guidelines that can guide AV developers and engineers in the design and development of AVs to ensure minimal perception errors. Additionally, it aims to guide management, researchers, and standard bodies in developing policies and standards that focus on improving the AV perception layer.

b) **Relevance Cycle**

The Relevance Cycle initiates DSR with an application context that not only outlines the requirements for the research as inputs but also defines acceptance criteria for the ultimate evaluation of the research results. Crucially, the DSR output, in this study, the developed guidelines, was returned to the application environment for evaluation within the automotive domain. The identified requirements for the guidelines were peer-reviewed by experts to validate and ensure the guidelines' design had a solid foundation. The individual component requirements served as inputs for the design cycle and were used to guide both data collection and evaluation of the guidelines.

c) **Design Cycle**

The internal Design Cycle of research activities iterates more rapidly than the Relevance and Rigour Cycles between the development of technological rules, the construction of an artefact, its evaluation, and subsequent feedback to refine the design further. The nature of this cycle is generating design alternatives and evaluating the alternatives against requirements until a satisfactory design is achieved. In this study, the design cycle involved the development and evaluation of preliminary guidelines. The subsequent feedback from the evaluation process was used to refine the preliminary guidelines to produce the final set of guidelines.

d) **Rigour Cycle**

The Rigour Cycle provides existing knowledge to the research initiative to ensure its innovation. As is contingent on researchers, this researcher thoroughly used extant literature as a knowledge base to guarantee that the guidelines produced were well-founded research contributions and not routine designs based on the application of well-known processes. Additions to the knowledge base, as a result of the DSR, included the methodologies and strategies integrated to guide this study, the new artefact (i.e. Guidelines), and all experience gained from performing the research (Hevner et al., 2004; Hevner, 2007). For the knowledge base, this study applied relevant existing literature to inform the development of guidelines.

2.5.2 DSR Artefacts

The resulting output of a DSR research is called an artefact, defined as an object made by humans with the intention that it is used to address a practical problem (Weigand, Johannesson and Andersson, 2021). DSR results in IS create a significant economic and societal impact (vom Brocke, Hevner and Maedche, 2020). A DSR artefact is designed to improve or build a solution to a problem, and it is considered complete and effective when it satisfies the requirements and constraints of the problem it was meant to solve (Hevner et al., 2004, Aparicio, Aparicio and Costa, 2023). Common artefacts include constructs, models, methods, and instantiations (Hevner et al., 2004; Baskerville et al., 2018; vom Brocke, Hevner and Maedche, 2020; Weigand, Johannesson and Andersson, 2021; Aparicio, Aparicio and Costa, 2023). These are briefly described in Table 2.2 below.

Table 2.2: Design Science Artefacts (adapted from Peffers et al., 2012; Vaishnavi et al., 2020)

Artefact	Description	Examples
Constructs	Defines the basic concepts and language in which problems and solutions are defined and communicated	Vocabulary and symbols
Models	Use constructs to represent the real-world contexts of the design problem and solution spaces	Abstractions and requirements
Methods	Defines a set of activities that can be used to achieve an intended goal.	Algorithm, guidelines and practice
Instantiations	Show that constructs, models, and methods can be implemented in a working system; they demonstrate feasibility, enabling concrete assessment of an artefact's suitability for its intended purpose.	Implemented and prototype systems

The guidelines (i.e. the artefact) developed in this study fall within methods, as they provide a set of activities to achieve the intended goal of minimising perception errors.

2.6 Design Science Research Methodology (DSRM) Process

The development of the set of guidelines as the potential solution to the research problem of this study is guided by the Design Science Research Methodology (DSRM) process. The

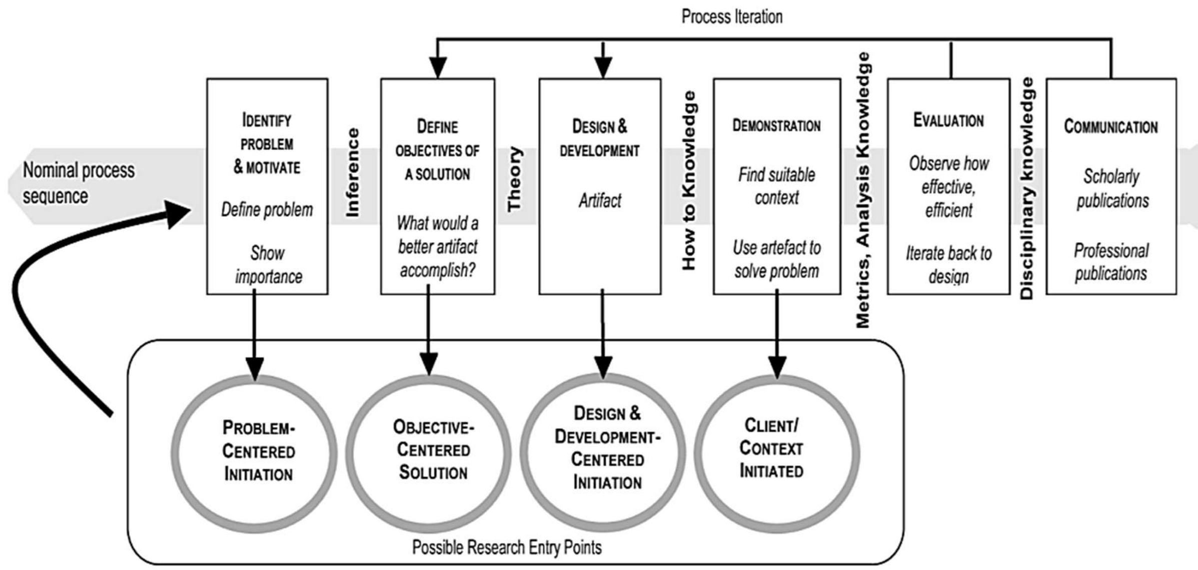

Figure 2.4: DSRM Process Model (adapted from Peffers et al., 2007)

DSRM process model, as presented in Figure 2.4, has six important activities, all of which will be accounted for in this study: problem identification and motivation, the definition of objectives, design and development, demonstration, evaluation, and communication. These activities are explained hereafter, and their application in this study will be further explicated in section 2.6.

Activity 1: Problem Identification and Motivation

This activity defines the specific research problem and justifies the value of a solution. Justifying the value of a solution accomplishes two things: it motivates the researcher and the audience of the research to pursue the solution, and it helps the audience to appreciate the researcher's understanding of the problem. A well-defined problem can be used to develop an effective artefact (Aparicio, Aparicio and Costa, 2023). The research problem stated in section 1.2 serves as the motivation for the construction of the guidelines. Additionally, the research problem was translated into research questions of this study (See section 1.3).

Activity 2: Define the objectives for the solution

The objectives of the solution can be inferred from the problem definition and knowledge of what is possible and feasible. The primary objective of this study was outlined in section 1.4 as motivated by the need for a solution to the research problem through the development of guidelines that can help minimise perception errors in AVs. This study was conducted to develop a solution suited to the automotive industry, particularly the AV perception layer.

Activity 3: Design and Development

This activity aims to create the actual solution or initial guidelines as motivated by activities 1 and 2. A DSR artefact can be any object in which a research contribution is embedded in the design. The development of the guidelines as the artefact of this study includes knowledge drawn from literature to inform the initial set of guidelines.

Activity 4: Demonstration

The DSR framework emphasises evaluation, requiring testing of the artefact in a suitable setting before detailed evaluation (Brunner et al., 2023). This activity demonstrates the use of the artefact to solve one or more instances of the problem, that is, how well the guidelines serve their intended purpose, and their relevance. Activities 4 and 5 are linked process activities because the metrics derived from the demonstration are evaluated in Activity 5. It is necessary to record adequate metrics and test the developed guidelines to prepare for the evaluation activity (Venable, Pries-Heje and Baskerville, 2012; Brunner et al., 2023).

Demonstration was accomplished in this study by conducting a thorough literature review, presented across Chapters 3 to 5, the results of which were utilised to determine the key requirements for the preliminary guidelines.

Activity 5: Evaluation

Evaluation is the crucial activity of the DSRM process (Hevner et al., 2004). Evaluation measures how well the artefact supports a solution to the problem. It involves comparing the objectives of a solution to actual observed results from the use of the artefact in context (Venable, Pries-Heje and Baskerville, 2016). Evaluation could take many forms, depending on the nature of the problem, venue and the artefact. In this study, evaluation occurred during Phase 2 of the DSRM application process. This was done by formulating an evaluation strategy using the Framework for Evaluation in Design Science (FEDS) to guide the evaluation of the initial guidelines to develop the final proposed guidelines (Venable, Pries-Heje and Baskerville, 2016).

The utility, quality and efficacy of the designed guidelines were rigorously demonstrated via well-selected and well-executed evaluation methods (Hevner et al., 2004). Table 2.4 presents the evaluation method types as presented by (Peffers et al., 2012).

Table 2.3: Evaluation Method Types (adapted from Peffers et al., 2012)

Method	Description
Logical Argument	An argument with face validity
Expert Evaluation	An assessment of an artefact by one or more experts
Technical Experiment	A performance evaluation of an algorithm implementation using real-world data, synthetic data, or no data, designed to evaluate the technical performance, rather than its performance in relation to the real world.
Subject-based Experiment	A test involving subjects to evaluate whether an assertion is true
Action Research	Use of an artefact in a real-world situation as part of a research intervention, evaluating its effect on the real-world situation.
Prototype	Implementation of an artefact aimed at demonstrating the utility or suitability of the artefact.
Case Study	Application of an artefact to a real-world situation, evaluating its effect on the real-world situation.
Illustrative Scenario	Application of an artefact to a synthetic or real-world situation aimed at illustrating the suitability or utility of the artefact.

Evaluating the rigour of the guidelines is a process that cannot be done by the researcher alone. For this reason, assessing the adequacy and comprehensiveness of the initial guidelines required the contribution of expert reviewers, as further discussed in section 2.10. The method of evaluation needed to fit the nature of the desired set of guidelines, and to provide feedback for further development and ensure the rigour of the study (Iyawa, Herselman and Botha, 2019). It is for these reasons that expert evaluations were chosen for this study.

As part of the evaluation activity, mixed-method data collection and analysis techniques were deployed. Data was collected through expert reviews using questionnaires comprised of both closed-ended and open-ended questions. The closed-ended questions provided quantitative data, and open-ended questions contributed qualitative data, aiming to provide richer context on the quantitative data (Saunders, Lewis and Thornhill, 2019). The study followed a descriptive data analysis approach facilitated by Excel and Power BI for visualisation.

Activity 6: Communication

All aspects of the problem and the designed artefact are communicated to the relevant stakeholders. This activity is where researchers communicate the problem and its importance, the artefact, its utility and novelty, the rigour of its design, and its effectiveness to researchers and other relevant audiences when appropriate (Hevner et al., 2004; Myllyoja et al., 2016; Aparicio, Aparicio and Costa, 2023). The researcher presented the preliminary guidelines at the South African Institute of Computer Scientists and Information Technologists (SAICSIT) 2024 conference. The feedback received from this presentation enriched the analysis process. Consequently, the research article presented at the SAICIT 2024 conference was published (see Appendix D). Pertaining to this study, the analysis of the results gathered during data collection was conducted. This led to the presentation of the final guidelines.

In reference to the DSR Framework presented in Figure 2.2, the output of this study is not only aimed at the application in the automotive industry in particular, AV development, but also adds to the Knowledge Base in the form of new knowledge learned through the process of developing this study. DSR must be presented effectively both to technology-oriented as well as management-oriented audiences (Hevner et al., 2004). The outcome of this study is communicated via this thesis, and the intended audience includes significant stakeholders such as AV developers, engineers, the management in the industry, and researchers. However, the thesis is broken down into multiple relevant chapters.

2.7 Application of DSRM Process

The iterative nature of the DSRM process was helpful to this study as it followed an incremental process to develop the final set of guidelines. It further allowed the researcher to explore different contexts and employ a variety of sources (viz. literature reviews and expert evaluations) to stimulate cooperation in building a meaningful solution (Peffers et al., 2007). It is through the DSRM process that the study emphasises rigour and relevance in research, ensuring that the guidelines artefact is both scientifically sound and practically useful. The DSRM process was applied in this study using a phased approach, presented in Figure 2.5 below.

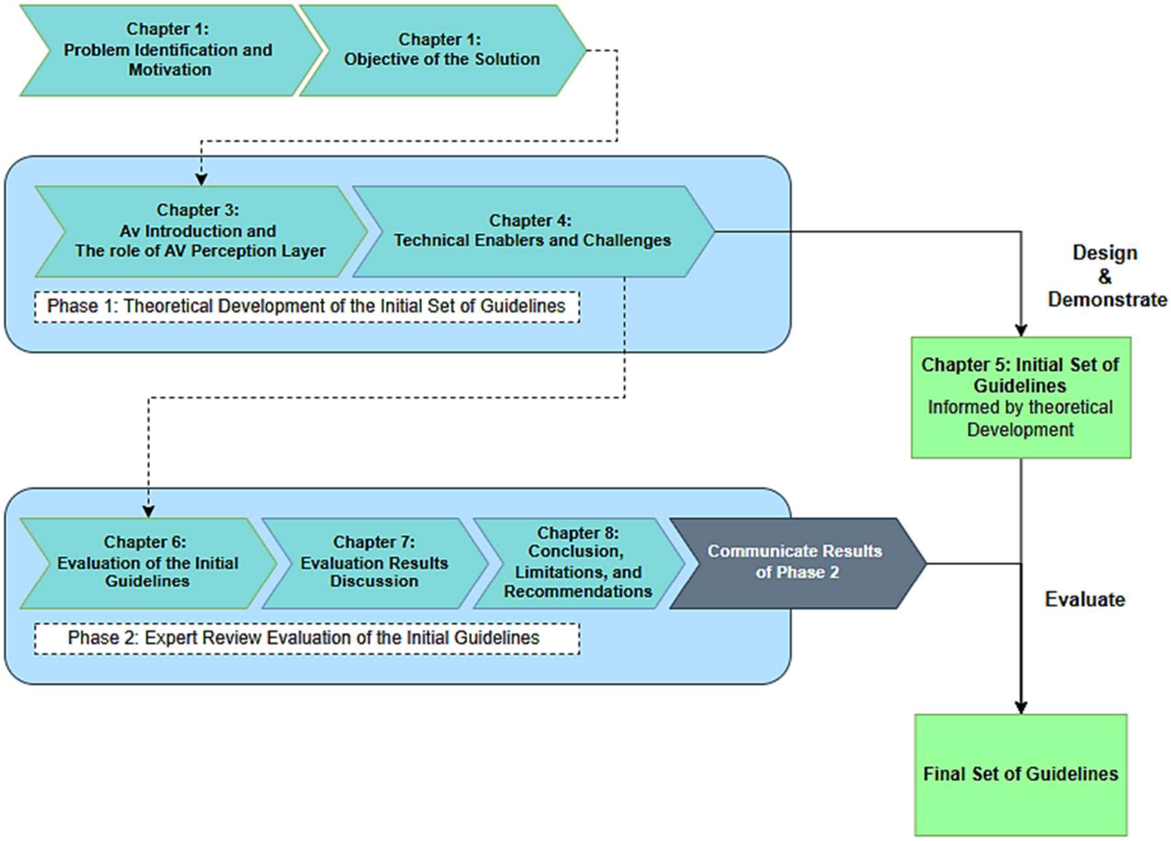

Figure 2.5: DSRM application process(adapted from Peffers et al., 2007; Myllyoja et al., 2016)

2.7.1 Phase 1: Theoretical Development of the Initial Set of Guidelines

This phase explores the knowledge base related to this study for the initial design of the guidelines. This activity resulted in a rigorous literature review. Literature review was an important part of this study as it provided an insight into existing work on AVs. The value of meaningful research is a "collective and cumulative endeavour" in which the contribution made by a researcher is based on prior knowledge that has been developed (Nakano and Muniz, 2018, p.1). According to the literature review, the minimum viable product approach is essential at the beginning of the DSR artefact design process (Brunner et al., 2023).

The literature review conducted in this study was a systematic literature review providing an in-depth analysis of literature in terms of AVs and the automotive industry at large. This study also considered prior literature on perception errors and the Autonomous Vehicle System Architecture (AVSA). The literature review and theoretical background are provided in chapters three (3) to five (5), each chapter addressing the key themes categorised according to research sub-questions. The data from the literature review was used to develop and define the initial guidelines in Chapter 5. The initial guidelines developed in phase 1 were evaluated through expert reviews in phase 2 of the DSRM application process.

Phase 1 Outcome: Design and demonstration of the initial Guidelines

The value of design in this study contributed to the overall objective of the research - developing guidelines as a research output. The literature review was used to develop and demonstrate the relevance of the guidelines. The purpose was to position and contextualise the abstract idea of the research in alignment with the relevant theory.

2.7.2 Phase 2: Expert Review Evaluation of the Initial Guidelines

Evaluation is an essential component of the DSRM process model. This phase focused on the validation and evaluation of the initial guidelines by experts, and the development of the finalised set of guidelines based on their feedback. A method of evaluation needs to provide feedback for further development and ensure the rigour of the research (Iyawa, Herselman and Botha, 2019). In this phase, expert review (questionnaire) was conducted as a way of gathering data to refine and design the final guidelines, which are the main contribution of this study.

Phase 2 Outcome: Evaluation of the initial guidelines to develop the final guidelines

The evaluation activity was intended to determine the effectiveness of the guidelines design in the automotive context. Moreover, evaluations were vital in ensuring that the guidelines were rigorous and aligned with the automotive industry knowledge base. The insights obtained from relevant expert reviewers played a valuable role in developing the finalised guidelines.

2.8 Research Strategy

As is the case in this study, case study research strategy is most relevant when (i) the form of the research question is “How” or “Why” (viz. “How” posed in this study), (ii) when the researcher has no control over behavioural events, and (iii) the focus of the study is a contemporary (as opposed to entirely historical) phenomenon (Yin, 2018, p32).

This study adopted a single case study research strategy to develop guidelines aimed at minimising vehicle perception errors within the context of AVs in South Africa. A case study allowed the researcher to understand the dynamics of the topic being studied within its setting or context (Saunders, Lewis and Thornhill, 2016). The case study strategy was appropriate in this study as it involves an in-depth study of phenomena in a real-life context, especially when the boundaries between phenomenon and context may not be clear (Saunders, Lewis and Thornhill, 2019; Chege and Otieno, 2020). A unit of analysis in case study research can come in various forms, such as individuals, organisations, an event, etc. (Grenier, 2023). South Africa served as the ideal unit of analysis in this study. It offers a unique context for studying AVs due to its diverse geographical and environmental conditions, road infrastructure challenges, and socio-economic complexities. The learnings from the South African context would inform the development of guidelines applicable not only to South Africa but also globally. However, it was noted that while it was unlikely that fully autonomous vehicles would be implemented in South Africa in the near future, it was imperative to align with current international developments in preparation for the development and deployment of AVs in South Africa, and to source expert evaluation within the global automotive industry (Van Straten and Andersen, 2023)

2.9 Data Collection and Analysis Techniques

Embedded mixed-method techniques were used in this study to develop and refine the initial set of Guidelines. Two data collection techniques were employed in this study: secondary data were sought from the literature, and primary data were collected using a questionnaire. These two methods were used during the demonstration and evaluation activities of the DSRM process (See section 2.5). During data collection, the researcher kept in mind the primary research question (RQ) of this study as introduced in Chapter 1:

"How can perception errors be reduced in Autonomous Vehicle System Architecture to improve safety and limit technical challenges?"

In considering the RQ, the remainder of this section describes how each technique was considered and the value of combining the two data collection techniques, and how this has assisted in generating more significant insights to refine the initial set of guidelines.

2.9.1 Secondary Data

This study used secondary data in Phase 1 of the DSRM application process. The research sub-questions were used to focus and guide this process, the goal being to define the theoretical foundation of the guidelines as presented across Chapters 3 to 5. The subsequent results were used to refine the constructs of the initial set of guidelines.

2.9.2 Expert Review (Questionnaire)

The design of the final guidelines to reduce perception errors in AVs required an evaluation of their effectiveness and relevance. Evaluation was crucial to DSR and required researchers to rigorously demonstrate the utility, quality, and efficacy of a design artefact using well-executed evaluation methods (Venable, Pries-Heje and Baskerville, 2012). Consequently, this study considered the insights of expert reviewers, as presented in the evaluation activity (section 2.5). This was done to assess the relevance and effectiveness of the guidelines and the potential value they could add to AVs and the automotive industry at large. The evaluation results were analysed descriptively.

2.10 Sampling Method

2.10.1 Expert Sampling Method

A non-probability purposive sampling method was used to select a limited number of experts who participated in phase 2 of the study to contribute their knowledge through questionnaires. Myllyoja et al. (2016) noted that, with purposive sampling, the researcher uses their judgment to select specific participants who can contribute to an understanding of the research problem and phenomena under investigation so as to achieve the goals of the research.

Purposive sampling is frequently utilised when working with relatively small samples, such as in case study research (Saunders, Lewis and Thornhill, 2019). The richness of the data collected matters more than the sample size. Case study research seeks to collect rich data rather than data that is statistically generalisable to a larger population (Yin, 2018). Guest, Bunce and Johnson (2006) recommended six to twelve participants for a qualitative study. Lopez and Whitehead (2013) stated that a common range for a qualitative study is eight to 15 participants. Drawing from these researchers, this study purposively selected 10 participants to evaluate the preliminary guidelines. Participants were chosen according to the criteria discussed above.

2.10.2 Expert Review Selection

A critical prerequisite for gaining expert insights was defining and outlining the criteria for selecting individuals to contribute to the study. An expert is an individual who possesses knowledge that can be applied at any given opportunity. These individuals "are able to think more effectively about problems" (Iyawa, Herselman and Botha, 2017, p7). This implies that for individuals to be considered experts, they must have sufficient knowledge regarding the subject matter at hand to enable them to make relevant (Iyawa, Herselman and Botha, 2017). Further, expert reviewers must possess an understanding of the subject matter and offer more valuable knowledge than an individual without a similar skillset (Allam, Flowerday and Flowerday, 2014).

Defining experts in this study was an interesting journey of discovery, as the topic is still emerging, especially within the South African context. However, beyond considering AV engineers, developers, and management involved in the development and deployment of AVs in South Africa, this study refined the expert's definition; the researcher considered individuals with knowledge of the overall automotive space who likely possess valuable insights into the South African context, regulations, infrastructure, and cultural diversity relevant to AV deployment and affecting AV perception. These individuals constituted 70% of the ten experts, while 30% were international reviewers who provided a broader understanding of AV technology development and potential challenges, compensating for any potential lack of in-depth knowledge within the South African context. Among the ten experts, two were from a South African automotive manufacturer, referred to as Company 2 in this study. An online platform, Prolific, was used to secure the remaining eight participants. The screening process on Prolific included participants from across all countries working within the automotive industry, resulting in eight responses. Consequently, three of the eight participants were not from South Africa, providing an invaluable global perspective.

2.10.3 Expert Review Instrument Development

A questionnaire, used as a data collection method, was administered to expert reviewers to evaluate the preliminary guidelines. Owing to the mixed-methods nature of the research method, the questionnaire contained both closed-ended and open-ended questions to promote in-depth exploration and eliciting detailed comments from the expert reviewers. The open-ended questions provided experts with the opportunity to elaborate on their responses, enriching the data gathered from closed-ended questions with valuable insights. As noted by Saunders, Lewis and Thornhill (2016), open-ended questions are particularly valuable in exploratory studies where detailed qualitative responses are necessary.

The approach for conducting the data collection process followed the general process of planning, designing, preparing, collecting, analysing data, and sharing findings (Yin, 2018). To ascertain the instrument's reliability, the study adapted and tailored instruments from other studies to address the research question (viz. Lehasa, 2018). The motivation for adapting instruments from other studies was to ensure that there was alignment between the overall purpose of the research and to further knowledge in this field of study. The process of adapting questions developed from other studies assisted the researcher to "compare findings" and assert the reliability of each question developed. Further, a pragmatic approach was taken to use an online platform, Prolific, to collect data using questionnaires as stated above so as to gain a global perspective on the quality of the initial guidelines.

2.11 Research Ethics

It was important for the researcher to gain permission from various gatekeepers before collecting data from the targeted global car manufacturers based in the Eastern Cape. The process of obtaining data from the various experts was guided by the human ethical guidelines regulated by the Rhodes University Human Ethics Committee (RU-HEC). The gatekeeper from Company 1 declined our request to collect data from their company, citing concerns about the potential disclosure of confidential company information and low staff morale. However, gatekeeper permission from the Head of Corporate Strategy at Company 2 was received. Furthermore, the study also used an online professional platform, Prolific, to collect data. The use of Prolific did not require gatekeeper permission, as the researcher approached the professionals in their professional capacity, not based on company affiliations.

2.12 Summary

The purpose of this chapter was to discuss the methodology used for this study. The study followed Design Science Research (DSR) as a theoretical lens, adopting the DSRM process as delineated by (Peffers et al., 2007). Table 2.4 below summarises the aspects considered for the development of the methodology chapter.

Table 2.4: Research Methodology Summary

Research Methodology Aspect	How it was applied in this study	Methods employed
Philosophy	Pragmatism	
Approach to Theory Development	Abductive Reasoning	
Methodological Choice	Embedded Mixed method	
Theoretical Lens	Design Science Research	
Strategy	Case Study	
	Design Science Research Methodology (DSRM) process	
	Framework of Evaluation in Design Science (FEDS) for evaluating the artefact of the research	Evaluation: - Constructs to evaluate were defined following the FEDS steps.
Data Collection	Secondary Data - Literature Review	Systematic Literature Review
	Primary Data: - Expert Review	Questionnaire
Data Analysis	Systematic Literature Review Results	Descriptive Analysis
	Questionnaire Results	

Chapter 3: Autonomous Vehicles

3.1 Introduction

This chapter presents an overview of the autonomous vehicle (AV) concept and outlines the tasks of the perception layer in the Autonomous Vehicle System Architecture (AVSA). It also covers the levels of automation and the system architecture before defining the perception layer tasks in automated driving. Understanding AVs and perception layer tasks aids in the development of the final guidelines of this study. This chapter is guided by RSQ1:

RSQ1: What should be the main tasks of the perception layer of the Autonomous Vehicles system architecture?

3.2 What is an Autonomous Vehicle (AV)?

The automotive industry is undergoing a drastic transformation. It is rapidly transitioning from the traditional concept of assembled mechanical parts controlled by humans towards innovative, connected, autonomous, and electric vehicles that offer a contextualised, intelligent, and customised customer experience (Pelliccione et al., 2017; Karmanska, 2021). Autonomous driving is anticipated to revolutionise road traffic by reducing accidents and congestion (Martínez-Díaz and Soriguera, 2018). The concept of AVs in transportation is still evolving (Kumar et al., 2022). Autonomy is the capability of an intelligent system to accomplish tasks in uncertain conditions in both its system and surroundings (Wang et al., 2020). Therefore, AVs are vehicles that can perceive, navigate, and carry out automotive functions independently, as described by Ahmed et al., (2022). These vehicles, also called autonomous or driverless cars, utilise sensors and software to operate and drive the vehicle (Rosique et al., 2019; Rana and Hossain, 2023). They have a modern electronic assistance system that can direct vehicles and park autonomously (Ondruš et al., 2020). However, autonomous technology is still not mature enough to handle very complicated scenarios (Wang et al., 2020), emphasising the need for effective ways to detect potential obstacles caused by other vehicles or other objects in the environment.

AVs support features like sensing the environment, internet connectivity, obeying traffic laws, autonomous navigation, efficient decision-making, ensuring safety for passengers and pedestrians, etc (Parekh et al., 2022). They aim to enhance transportation by reducing accidents, traffic congestion, and carbon emissions, as well as improving mobility for individuals with disabilities and the elderly. 86% of the total road fatalities in South Africa are attributed to human factors like distractions, speeding, intoxication, emotional driving, and/or fatigue. This statistic remains fairly uniform across the globe. The National Highway Traffic Safety Administration (NHTSA-USA) survey indicated that 94% of accidents result from human-related errors (Van Brummelen et al., 2018; Uys, Van Belle and Lees, 2022). For these reasons, the manual operation of motor vehicles is coming increasingly under criticism amidst the growing fascination with autonomous technologies in vehicles. When discussing AVs, it is important to consider the centrality of automation levels, which serve to measure the technological advancement of AVs (Rosique et al., 2019).

3.3 Automation Levels

Various standards for measuring the level of AV automation have been defined using the six-level classification definition by the Society of Automotive Engineers (SAE) International. The six levels are widely adopted by automobile manufacturers, regulators, and policymakers (Wang et al., 2020). The definition of automated levels by SAE includes six automation levels (Levels 0-5), as described in Table 3.1 below.

Table 3.1: Automation Levels (adapted from Yeong et al., 2021)

Level (SAE)	Type		Description
0	No Automation	Human Supervision	A human driver performs all driving tasks
1	Driver Assistance		The human driver controls the vehicle, but the automation system assists in driving.
2	Partial Driving Automation		Combined automated functions are applied in the vehicle, but the human driver still monitors the environment and the controls of the vehicle.
3	Conditional Driving Automation	Machine Supervision	The human driver only takes over when necessary.
4	High Driving Automation		The automation system can drive automatically under given conditions. However, the human driver can still control the vehicle's operations.
5	Full Driving Automation		The driving is fully autonomous under all conditions, and the human driver may be able to control the vehicle. The driving is fully autonomous under all conditions, and the human driver may be able to control the car.

The categorisation of automation levels is determined by how the automation system and human driver work together to manage various driving tasks such as monitoring the environment, dynamic driving tasks fallback, steering and throttle control, and the system's capacity for different autonomous driving modes. The level of automation is also defined by how much the Advanced Driver Assistance Systems (ADAS) relieve human tasks. ADAS includes features like automated parking, cruise control, and hazard alerts (Rana and Hossain, 2023). As vehicles become more autonomous, the complexity of ensuring system stability, reliability, and safety increases. A key distinction is between level 2, where the human driver performs part of the dynamic driving task, and level 3, where the automated driving system performs the entire dynamic driving task. The term "dynamic driving task" includes the operational (steering, braking, accelerating, monitoring the vehicle and roadway) and tactical (responding to events, determining when to change lanes, turn, use signals, etc.) aspects of the driving task, but not the strategic (determining destinations and waypoints) aspect of the driving task (Rana and Hossain, 2023).

Presently, most vehicles available to the public in South Africa are at either level 1 or 2 due to sensor limitations and high costs (Wang et al., 2020; Ahmed et al., 2022; Uys, Van Belle and Lees, 2022). In the United States of America (USA), levels 1-3 are commercially available (Resnik and Andrews, 2024). However, several applications of level 4 have been developed, with some organisations implementing pilot projects to test AVs in specific scenarios (Resnik and Andrews, 2024). There are a few level 4 vehicles that were released as of 2023, showcasing progress, but achieving level 5 will require years of development, testing, and approval (Ahmed et al., 2022; Wang et al., 2020; Rana and Hossain, 2023; Hurair, Ju and Han, 2024; Wang et al., 2021). Tesla sold over 800 000 vehicles with advanced autopilot and self-driving functions. The Tesla vehicle can drive itself, but the human driver must monitor the vehicle's performance and be prepared to take over driving functions (Resnik and Andrews, 2024). These vehicles can be classified as a level 4 vehicle. Despite advancements, further training is needed in all scenarios to prevent malfunctions and crashes (Ahmed et al., 2022). Companies and researchers have made efforts to reach level 5 automation, but the complexity and challenges from levels 0 to 4 hinder the development of level 5 vehicles, requiring more research and experimentation (Hurair, Ju and Han, 2024).

Various South African manufacturers have made attempts and significant progress in successfully achieving level 2 automation. Table 3.2 presents a list of South African manufacturers and the related technologies they employed to attain automation level 2.

Table 3.2: South African Manufacturers and SAE Level 2 Functionalities (adapted from Uys, Van Belle and Lees, 2022)

Manufacturer	Technology Package	Technology Descriptions
BMW	Extended Traffic Jam Assistant	- Driving Assist - Active Cruise Control - Parking Assist
Mercedes-Benz	Intelligent Drive	- Distronic (Active Distance Assist) - Active Lane Tracking & Lane Changing - Active Steering & Blind Spot Assist
Toyota	Toyota Safety Sense	- Blind Spot Monitoring - Lane Keeping Aid & Departure Alert - Pre-Crash System - Adaptive Cruise Control

Volkswagen	Driver-Assistance Systems	- Adaptive Cruise Control - Blind Spot Detection - Rear traffic Assist
Volvo	IntelliSafe	- Lane Keeping Aid - Automated Collision Avoidance - AutoBrake - Blind Spot Information with Steering Assist - Distance Alert & Pilot Assist (Automated Lane Changing)
Ford	Co-Pilot360	- Automatic Emergency Braking - Adaptive Cruise Control - Lane Keeping Assist
Nissan	Intelligent Mobility / ProPILOT	- Automatic Emergency Braking - Blind Spot Warning - Moving Object Detection - Intelligent Lane Intervention
Renault	Highway & Traffic Jam Companion	- Emergency Brake Assist - Blind Spot Warning - Parking Assist
Subaru	EyeSight	- Pre-collision braking - Adaptive Cruise Control - Lane Departure & Sway Warning - Lead Vehicle Start Alert - Pre-collision Throttle Management

The degree of safety of AVs is directly influenced by the dependability of the AVSA and its associated hardware and software. Importantly, the AVSA is contingent upon the degree of automation employed, such that the safety of AVs may exhibit divergent patterns at varying levels of automation (Wang et al., 2020). Moreover, even at the same level of automation, the system architecture of AVs can differ across various studies (Betz et al., 2019; Rosique et al., 2019; Wang et al., 2020).

3.4 Autonomous Vehicle System Architecture

The AVSA design consists of a sensor-driven perception layer, a decision layer based on algorithms, and an actuator-based action layer, along with the connections between them, as illustrated in Figure 3.1. These are the three essential tasks for autonomous driving (Betz et al., 2019, Wang et al., 2020, Wang, 2021).

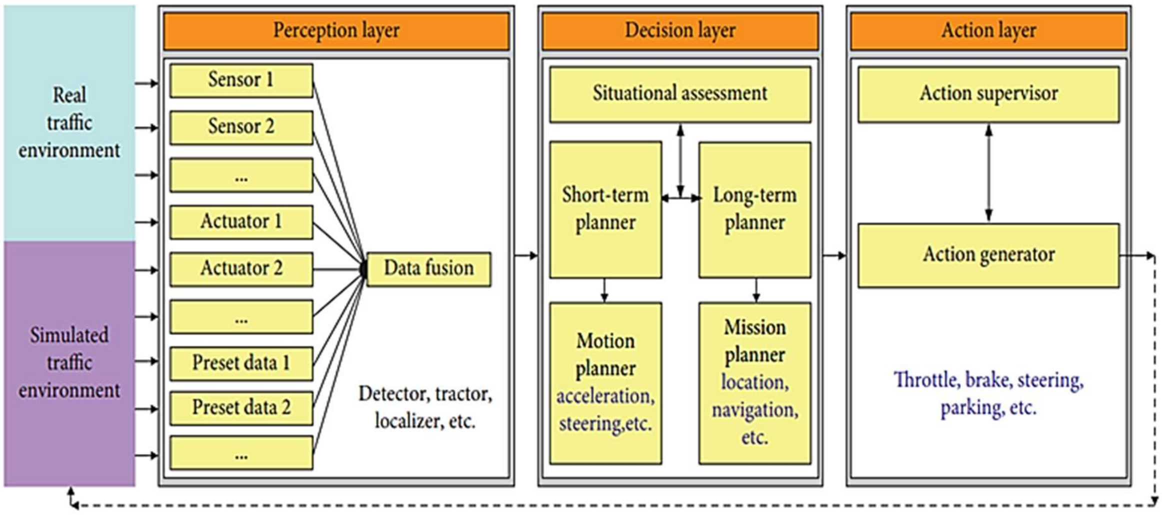

Figure 3.1: Autonomous Vehicle System Architecture (adapted from Wang et al., 2020)

3.4.1 Perception layer

Perception is critical in facilitating autonomous driving (Cunneen et al., 2020). The perception layer in AVs refers to the component responsible for gathering and interpreting information about the vehicle's surroundings for real-time decision-making (Rosique et al., 2019; Wang et al., 2020). This component is essential for the proper functioning of AVs, as it enables them to determine their position and navigate through their environment accurately (Khan et al., 2022). The perception layer acts as the "eyes and ears" of AVs. The perception layer consists of various sensors and systems that work together to perceive the environment and gather information from different sources to navigate safely and effectively in complex real-world environments (Rosique et al., 2019). AVs must independently perceive the environment to gain the necessary data to make effective decisions.

The perception layer can be broadly categorised into two main components: environmental perception systems and localisation. The environmental perception system is responsible for converting the physical world data into digital signals, which serve as the basis of the hardware architecture of AVs (Betz et al., 2019; Rosique et al., 2019; Braud et al., 2021). Localisation, also referred to as Simultaneous Localisation and Mapping (SLAM) (Braud et al., 2021), plays a critical role in the development and implementation of AVs, as it enables these vehicles to determine their position and navigate through their environment accurately (Khan et al., 2022). Localisation aims to build and update an unknown map while simultaneously tracking the AV's position and orientation (Braud et al., 2021). Depending on the level of vehicle automation, the perceived data may also come from the communication between the AVs and the corresponding infrastructure, other vehicles, the internet, and the cloud (Wang et al., 2020; Braud et al., 2021).

The perception system collects data about the vehicle's surroundings using advanced sensing technologies such as light detection and ranging (LiDAR) sensors, cameras, radio detection and ranging (RADAR), ultrasonic, and global positioning system (GPS) (Rosique et al., 2019). However, challenges like fluctuating lighting and adverse weather, discussed in Chapter 4, can cause failures that affect decision-making (Van Brummelen et al., 2018). The layer's ability to gather information from multiple sources and construct an understanding of the environment is essential for the safe and efficient functioning of AVs (Khan et al., 2022). Hence, the perception layer is a critical component of AVs, and its effective operation is necessary for the successful adoption of autonomous driving technologies. It directly impacts AVs' planning and decision-making, allowing them to react to environmental events accordingly (Malik et al., 2023). The more accurate the data observed is, the better AVs make decisions. The perception layer relies on sensors to gather necessary data. The data gathered can also come from communication with other vehicles, pedestrians, and other objects in the surroundings.

3.4.1.1 ***Sensors***

AVs utilise sensors to collect information and operate autonomously. Sensors are devices that transform environmental events into measurable data for processing (Ignatious, Sayed and Khan, 2022). AVs detect obstacles, vehicles, traffic signals, pedestrians, and infrastructure using different sensor technologies for safe driving.

In AVs, sensors are critical to the perception of the surroundings and localisation of the vehicles for path planning and decision-making, essential precursors for controlling the vehicle's motion. The accuracy and reliability of sensors and the perception layer directly affect driving safety and AVs (Su, 2023). Sensors such as Global Navigation Satellite System

(GNSS), Inertial Measurement Unit (IMU), and vehicle odometry sensors are used to determine the relative and absolute positions of the vehicle. The relative localisation of an AV refers to the vehicle referencing its coordinates concerning the surrounding landmarks. In contrast, absolute localisation refers to the vehicle referencing its position concerning a global reference frame (world) (Yeong et al., 2021). The sensors sense and acquire information such as distance measurements or light intensity from the surroundings of the system. AVs primarily utilise multiple vision cameras, RADAR sensors, LiDAR sensors, and ultrasonic sensors to perceive their environment. AVs also utilise other sensors, such as GPS and high-definition cameras, to record the position of the car and review other elements of the traffic around it (Yeong et al., 2021; Ahmed et al., 2022). Table 3.3 presents the different sensors used in AVs, their advantages and limitations, and their application.

Table 3.3: Sensors and their advantages, limitations, and applications (adapted from Khatab et al., 2021)

Sensor	Advantage	Limitations	Applications
Monocular Camera	- Low cost - Different Fields of view - High-resolution cameras provide a longer range - Provide features data	- High computational requirements - Does not provide straightforward distance calculations - Limited by weather and lighting conditions - Cannot calculate the velocity of objects	- Object detection & classification - Traffic signal recognition - Road and lane detection
Stereo camera	In addition to the advantages of monocular cameras, stereo cameras also provide: - Depth calculation	- More expensive than molecular cameras	- Object detection & classification - 3D localization - 3D mapping

	- 3D-localization of objects - Enhanced object detection	- Higher computational requirements - Limited by weather and lighting conditions - Cannot calculate the velocity of objects	
Short-range RADAR	- Large Field of View - Easier to develop - Resistant to bad weather	- Large package size - Shorter sensing range	- Blindspot detection - Parking aid
Long-range RADAR	- Higher accuracy - Between resolution - Smaller package size	- More data losses - Narrow Field of View at short distances	- Speed calculation of detected vehicles - Used on highways and cross-traffic alert systems
Ultrasonic	- Direct distance estimation - Can operate in harsh weather conditions - Can detect near objects (< 2m)	- Can only detect near objects - Low angular resolution	- Parking assistance - Near object detection

Sensors play a significant role in the AVSA. Sensor degradation and malfunctions can lead to perception errors or incorrect decision-making, without a reliable sensing technology that potentially provides a solution (Wang et al., 2020). Figure 3.2 illustrates the type and placement of primary sensors (cameras, LiDARs, and RADARs) in automated vehicles for environmental perception.

In summary, the sensors installed in AVs play a vital role in enabling the vehicles to operate independently and safely. The sensors acquire and process information about the surroundings, which is then used to make decisions about steering, acceleration, and braking. Sensors work together to provide a comprehensive view of the environment. The data acquired by sensors acts as an input for the perception layer. The accuracy and reliability of the sensors are crucial in ensuring driving safety and avoiding accidents.

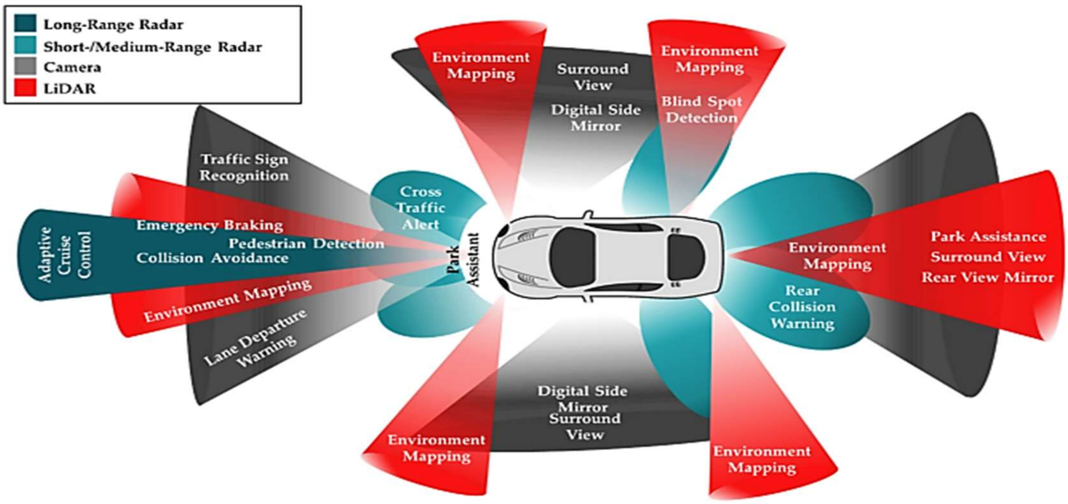

Figure 3.2: AV sensors overview (adapted from Yeong et al., 2021)

3.4.1.2 ***Vehicular Communication***

It is crucial for AVs to be connected and share environmental data. In addition to sensor data from the environment, vehicle-to-everything (V2X) communication is vital for vehicles to exchange information, leading to a more accurate perception. This enhances automated vehicle perception and action (Braud et al., 2021). Access to external data improves decision-making in AVs (Khan et al., 2022). V2X communication is a combinational form of vehicle-to-vehicle (V2V), vehicle-to-person (V2P), vehicle-to-infrastructure (V2I), vehicle-to-network (V2N), and vehicle-to-cloud (V2C) communications, as shown in Figure 3.3 below (Ekatpure, 2023; Hasanujjaman, Chowdhury and Jang, 2023). The integration of vehicle communication with the internet transforms public transportation, enhancing its effectiveness and sustainability. Various road users, such as drivers, pedestrians, cyclists, and construction workers, interact to coordinate movements and preserve road safety in AVs. Communication methods may include pedestrian gestures, facial expressions, and vehicular devices (Wang et al., 2020).

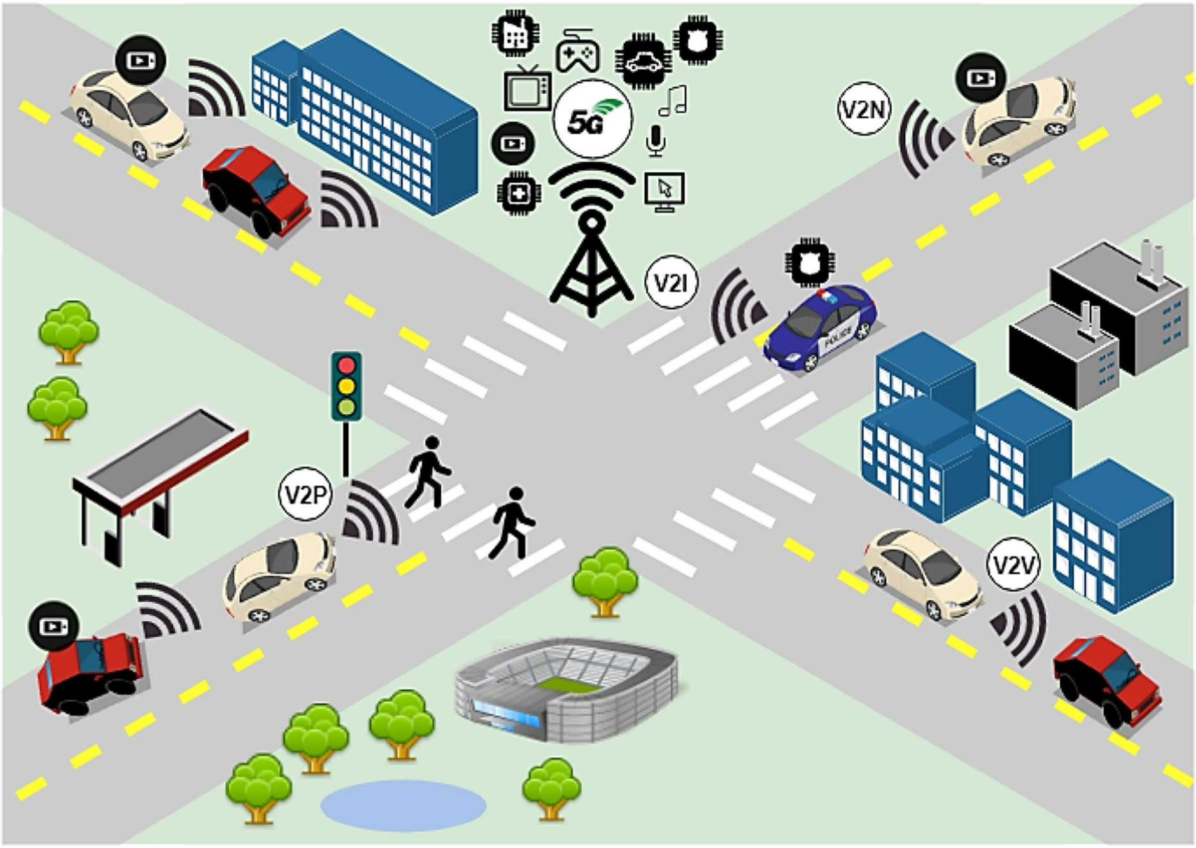

Figure 3.3: V2X Environment (adapted from Storck and Duarte-Figueiredo, 2019)

3.4.2 Decision layer

AVs need to be capable of making appropriate decisions in all traffic conditions to guarantee safety. Decision-making is crucial for automated driving and is carried out through planning algorithms (Malik et al., 2023). Decision-making for autonomous driving is required in dynamic and uncertain environments (Eraliev et al., 2022). The decision layer, also known as the planning layer (Betz et al., 2019; Rosique et al., 2019; Braud et al., 2021), is responsible for making relevant decisions and providing actionable instructions to reach a desired goal. The decision layer utilises information from the perception layer to analyse the driving situation, including the position of other vehicles, road conditions, and potential obstacles (Rosique et al., 2019; Wang et al., 2020). Additionally, it ensures that the planned trajectory aligns with the vehicle's physical capabilities and control constraints (Betz et al., 2019).

Situational awareness is crucial for decision-making in both short-term and long-term planning within the automated driving system. Short-term planning includes trajectory generation, obstacle avoidance, and event and manoeuvre management, while long-term planning involves mission and route planning (Wang et al., 2020). The decision layer incorporates algorithms prioritising collision-free driving as the main objective while also considering secondary goals like maximising range or completing track sections quickly. These algorithms utilise sensor data to make decisions based on the current driving scenario (Betz et al., 2019). However, due to the still maturing AV technologies, human drivers must take control and supervise the driving process when the system fails or is limited in performance (Wang et al., 2020).

The decision layer consists of three sub-layers: mission planning, behaviour planning, and motion planning, each focusing on different aspects of planning (Rosique et al., 2019; Wang et al., 2020; Braud et al., 2021; Gao et al., 2022).

a) **Mission planning**
   Mission planning is also referred to as route planning or path planning. It focuses on task-level planning, such as selecting a path between a starting point and a destination.
b) **Behaviour Planning**
   This sub-layer focuses on short-term objectives, such as ensuring that a vehicle adheres to traffic rules and interacts safely with other vehicles while proceeding toward the mission planner's objectives.
c) **Motion planning**
   The motion planner's goal is to implement the behaviour planner's decision. This sub-layer refers to the process of establishing an appropriate path and deciding on a set of activities to achieve a certain goal. This series corresponds to a specific goal, such as accelerating and avoiding obstacles.

3.4.3 Action layer

The action layer, also referred to as the control layer, guides the vehicle to execute the control signals generated by the decision layer on a physical level (Braud et al., 2021). When the vehicle has completed its self-positioning and formulated the decision based on the data from the perception layer, it translates the AV intentions into actions by taking the generated decision from the decision-making component and applying them to the physical control systems of the AV, for example, steering, throttle, and braking (Gao et al., 2022; Malik et al., 2023). The action layer mainly controls the steering wheel, brake, and throttle of the vehicle according to the decisions made by the decision layer (Su, 2023). Vehicle control involves both lateral and longitudinal control. Lateral control involves steering wheel and tire lateral force adjustments, while longitudinal control pertains to vehicle acceleration and braking (Braud et al., 2021; Gao et al., 2022; Khan et al., 2022).

The effective detection of hazards caused by other road users is crucial for AVs to make active decisions to avoid oncoming accidents. AVs should decide if they need to take actions that may violate traffic regulations to avoid potential fatal or injurious accidents (Wang et al., 2020).

In conclusion, the AVSA in Figure 3.1 functions by receiving data from the real world or a simulated traffic environment through sensor technologies. The perception layer creates a virtual map of the environment using the sensor data and information received from V2X communication, sending it to the decision layer. The decision layer processes the information to make decisions for the action layer, which then executes the actions for the vehicle. Precise data gathering, processing, and communication are essential for driving safety in AVs (Ahmed et al., 2022).

3.5 Perception Layer Task

The role of perception is crucial in the development of safe AVs (Betz et al., 2019; Wang et al., 2020; Wang, 2021; Ahmed et al., 2022).. AVs create perception by processing different types of information from different sensors (Khan et al., 2022). This study developed guidelines for minimising perception errors in AVs to enhance the safety and reliability of autonomous driving. It is crucial to comprehend and outline the key tasks of the perception layer in AVs to develop a pertinent and significant artefact. Figure 3.4 presents perception layer tasks identified from the literature.

Figure 3.4: Perception layer tasks (Author's own work)

3.5.1 Object detection and classification

Object detection allows AVs to perceive and be aware of their surroundings to make accurate and safe decisions in response to detected objects (Yu, 2025). AVs must be able to detect the surroundings, interpret, and form an understanding of the environment just as humans would in traditional vehicles. Apart from sensing and data interpretation, AVs must determine the nature of the objects and predict their behaviour. They require cognitive abilities to categorise objects based on their nature and characteristics. They recognise and classify the objects in the environment based on their characteristics and behaviours (Wang et al., 2020), and they must also predict the trajectories of other vehicles (Su, 2023). Classification helps to know what the detected object is and how to deal with it. Machine vision can potentially surpass human drivers in low-visibility situations (Szűcs and Hézer, 2022). Object detection is a critical task in AVs due to the diverse types of objects that can pose challenges in changing environments. These objects can be dynamic objects, such as pedestrians, cyclists, and other vehicles or static objects such as traffic signs, buildings, bridges, and other forms of landmarks (Ondruš et al., 2020;

Khatab et al., 2021; Vargas et al., 2021). This information becomes crucial for decision-making and planning the vehicle's actions.

3.5.2 Lane Detection and Tracking

Lane detection and tracking involve the identification and monitoring of road lanes to aid in vehicle navigation and safety. The goal is to ensure that vehicles stay in their assigned lane and avoid collisions with vehicles in adjacent lanes (Zakaria et al., 2023). AVs utilise sensors and positioning systems to monitor lane markings on the road (Ahmed et al., 2022). A key aspect of AVs is the real-time identification of lanes and tracking curves, influencing control based on lanes and curves (Pavel, Tan and Abdullah, 2022). Tracking also includes real-time tracking achieved by detecting objects consecutively on different frames (Boukerche and Sha, 2021).

3.5.3 Real-Time Feedback

Real-time updates apply to V2X communication as this also fits data to the decision layer. Primarily, this task is aimed at that as access to external data improves decision-making in AVs (Khan et al., 2022). Furthermore, the key to decision-making is real-time and reliability. The transfer of information from the perception layer to the decision layer is crucial for decision-making and path planning. The perception layer conveys the surroundings' insights to the decision layer, needing to supply precise and current environmental information (Betz et al., 2019). It is crucial to consistently update the transmitted data to prevent inaccurate decisions that can pose risks. This task is vital as real-time decisions depend on the perceived information for decision-making algorithms.

3.5.4 Assess potential obstacles

The perception layer not only identifies obstacles but also evaluates and understands their nature and depth, ensuring the safety of AVs by monitoring the environment for hazards and reacting accordingly (Ondruš et al., 2020). Additionally, it comprehends traffic conditions and lane curves (Khan et al., 2022). Evaluating potential obstacles assists AVs in recognising dangerous situations and responding accordingly (Szűcs and Hézer, 2022). The decision layer relies on such information to make decisions. This assessment is vital as AVs might have to make decisions that could be fatal or violate traffic regulations, as stated in section 3.4.3. In some cases, AVs must determine whether to violate traffic regulations to prevent potentially fatal accidents (Wang et al., 2020).

3.5.5 Sensor data fusion

The perception layer gathers data from various sensors to understand environmental conditions for immediate decision-making. These sensors work together to provide a comprehensive view of the environment (Ondruš et al., 2020; Wang et al., 2020). Sensor data fusion aims to improve the measurement of two or more data sources from sensors beyond the individual measurement of each of them. Sensorial fusion applied to the measurement of redundant data reduces the uncertainty of the measurement and improves the accuracy and integrity of the system, improving fault tolerance (Rosique et al., 2019). The importance of sensor fusion lies in the challenge posed by conflicting information from multiple sensors in AVs, which hinders the computer's ability to make decisions (Kumar et al., 2022).

3.5.6 Dynamic adaptation

Based on the researcher's observation, researchers often overlook this task. The perception layer must continuously update itself and refine perception algorithms and models based on real-world data and feedback from on-road testing (Wang et al., 2020). This task is essential in executing other sub-tasks, such as assessing potential obstacles, similar to how drivers in traditional vehicles rely on experience to handle obstacles easily. AVs must also continuously update themselves based on their own experiences or those of others. The development of this advanced perception layer enables AVs to better adapt to the complex traffic environment and respond accordingly (Su, 2023).

3.5.7 Localisation

The concept of localisation in AVs refers to accurately determining the vehicle's exact position to know where the AV is in a given scene. This includes estimating the position of objects in the surrounding area and self-localisation (Bachute and Subhedar, 2021). This aspect is significant in the realm of autonomous driving, as the vehicle's navigation is crucial for dictating its movements (Nahata and Othman, 2023). The perception layer uses sensor data to capture the position of the vehicle and external environment information (Wang, 2021), interpreting sensor data to understand the position, speed, and orientation of the vehicle (Rosique et al., 2019).

Localisation and environmental perception are vital for path planning and decision-making (Yeong et al., 2021; Ignatious, Sayed and Khan, 2022).

3.6 Summary

This chapter defined AVs, the levels of automation, the AV system architecture, and explored the different layers of the architecture. Furthermore, it outlined and elaborated on the seven key tasks performed by the perception layer within the broader AV system architecture and its contribution to the overall AV functionality. The outlined roles are Object Detection and Classification, Lane Detection and Tracking, Real-Time Feedback, Assessing Potential Obstacles, Sensor Data Fusion, Dynamic Adaptation, and Localisation. AVs present several opportunities that can benefit developing countries, including South Africa. However, several challenges impede the widespread deployment of fully autonomous vehicles, which are addressed in the subsequent chapter.

Chapter 4: Technical Enablers and Challenges

4.1 Introduction

This chapter defines perception errors and provides an overview of the factors that challenge the perception layer, leading to perception errors. This chapter further provides important factors that can help in addressing these challenges. Furthermore, it provides how these challenges affect perception tasks. This chapter is guided by RSQ 2:

RSQ2: What are the technical enablers and challenges encountered in autonomous vehicles?

4.2 What are Perception Errors?

4.2.1 Definition

Perception errors refer to any perception inaccuracies that can lead to unsafe driving behaviour and potentially cause collisions. These errors can be categorised as false negatives and false positives. False negative errors refer to instances where the perception system fails to detect an object, while false positive errors happen when the perception system reports a non-existent object (Oboril et al., 2022). Perception errors may involve providing incorrect distance or velocity values, which can result in misjudging the proximity or speed of objects on the road (Oboril et al., 2022). While it is desirable for a fault-free perception layer under any conditions, so far, it has been hard to guarantee it. There are three main sources of perception errors in autonomous vehicles (AVs). Perception errors may be due to AV hardware, software, or communication limitations or challenges (Wang et al., 2020). Section 4.3 discusses factors that potentially cause perception errors, including environmental conditions, ethical, legal, and societal considerations, sensor limitations, and processing requirements challenges.

4.3 Overview of AV Perception Layer Challenges and Limitations

The safety and reliability of AVs are very critical issues. The instability of AV technology and vulnerabilities in the system may lead to serious safety accidents and traffic chaos (Wang et al., 2020; Szűcs and Hézer, 2022). According to Marole et al. (2023), the safety and security issues related to transportation have been a persistent problem in South Africa. Although South Africa continues to learn from international best practices, there is a need for solutions tailor-made for South African transport and related problems. AVs may help developing nations such as South Africa with transportation issues, such as lowering traffic congestion, enhancing safety, and expanding access to transportation for those who do not currently have it (Sadaf et al., 2023). Improving the safety and reliability of AVs requires research to improve the perception, decision, and control systems, as well as research focusing on legal and moral issues related to AVs. However, the main emphasis of this study is on the perception layer. This section introduces core challenges and limitations associated with the perception layer, leading to perception errors. These challenges and limitations affect the overall AV development globally and sometimes overlap.

4.3.1 Sensor limitations and failures

Sensor technologies play a crucial role in AV perception. The primary role of sensors is to accurately capture real-time environmental information for the AV system (Liu et al., 2020). Currently available sensors struggle to operate accurately due to limitations that hinder the accurate perception of AVs (Tiusanen, Malm and Ronkainen, 2020). These limitations are not often clear, but the sensor's capability gradually deteriorates as conditions worsen (Tiusanen, Malm and Ronkainen, 2020). Nevertheless, any failures could result in dangerous driving behaviours. Any errors in the perception of the vehicle status, location, and movement of other road users, traffic signals, and other hazards may raise safety concerns for AVs (Wang et al., 2020). Alatise and Hancke (2020) studied the challenges of autonomous mobile robots. They reported that potential safety issues arise if a mobile robot cannot observe its environment correctly and efficiently to perform tasks such as estimating the position of an object accurately. This underscores the need for effective and reliable sensor technologies, as they can limit the quality and range of a vehicle's perception (Ignatious, Sayed and Khan, 2022).

Several factors could lead to sensor failures. Sensors may fail due to bad calibration, inaccurate readings, or physical or electrical failures (Realpe, Vintimilla and Vlacic, 2016; Ignatious, Sayed and Khan, 2022). Another significant challenge is determining the best approach to handle faulty and unreliable communication errors (Ignatious, Sayed and Khan, 2022). Another issue is the selection of appropriate hardware and operating infrastructure, deployment, programming model, and synchronisation. An additional challenge faced by most sensor manufacturers is developing reliable and robust designs of smart sensors for accurate and precise measurements. Various sensors installed on AVs possess different strengths that complement each other. Nonetheless, the problem with so many sensors is that they sometimes contradict, making it difficult for the computer to prioritise (Kumar et al., 2022). Sensor data accuracy depends on the environmental stimuli to perceive the scene, and environmental factors such as adverse weather conditions can lead to sensor failures and inaccurate data (Mohammed et al., 2020).

Various studies suggest robust sensor fusion algorithms (as discussed in section 4.6.2.2) as a potential solution to overcome some of the sensor limitations and failures encountered. This study suggests sensor calibration and maintenance as an additional solution, as discussed in section 4.6.2.3. Environmental factors and inadequate infrastructures often lead to sensor inaccuracies and failures.

4.3.2 Environmental Factors and Road Infrastructure

Various environmental factors, including low visibility, adverse weather conditions, and occluded and distant objects, impact the perception accuracy of AVs (Boukerche and Sha, 2021; Khatab et al., 2021). Adverse weather conditions such as snow, fog, and rain present a major challenge for AVs in object detection as they hinder the sensor's ability to capture information about the surroundings, impeding their functionality (Hasanujjaman, Chowdhury and Jang, 2023; Nahata and Othman, 2023). For instance, bad weather can decrease the visibility of traffic signs, and an obstacle can partially obscure road signs, potentially even making an experienced human driver miss important signs. Under autonomous technologies, as they are expected to supersede human drivers, traffic and sign recognition technologies must be good at classifying road signs (Mohammed et al., 2020). Handling these adverse weather conditions is a key challenge (Katiyar, Shukla and Chawla, 2024).

Environmental factors are the most common cause of sensor failures in the currently available sensors. Conditions such as inadequate lighting and a night setting produce poor results. AVs require standard definitions for various outdoor conditions (Tiusanen, Malm and Ronkainen, 2020; Zakaria et al., 2023). Waymo (2023a) indicated that various environmental factors affect AV perception. It is important to study the effect of the conditions on sensors through simulations to inform and design the appropriate sensor cleaning mitigation for these conditions. The best way to overcome some of the challenges caused by difficult weather conditions is to have active sensor cleaning and self-calibration mechanisms, such as wipers and air puffers (Ekatpure, 2023). An example of this could be how wipers operate in traditional vehicles. The same strategies could be suitably implemented in AV sensors.

The deployment and development of AVs in South Africa, as well as most other developing economies, are hindered by poor road infrastructure and unpredictable traffic patterns (Kumar et al., 2022; Ekatpure, 2023; Zhou, 2025). All these factors affect AV perception and raise safety concerns. South Africa requires an efficient and effective road network for AVs (Pillay, 2023). It faces challenges in handling adverse weather and road conditions in traditional vehicles, as well as in communicating with other vehicles and detecting objects in AVs (Carzar, 2020). Potholes across South Africa's ageing road infrastructure are a big concern. The presence of potholes, as well as uneven surfaces and the general lack of proper road markings, can severely hinder the ability of the sensors (Ekatpure, 2023). The government must improve road infrastructure for autonomous driving safety (Pillay, 2023). On the contrary, a reliable computing system must be employed to overcome these challenges effectively.

4.3.3 Computational complexity and processing requirements

Maintaining high accuracy while ensuring real-time processing is a key challenge in AVs for object detection (Yu, 2025). The perception layer must provide real-time updates and feedback to the decision layer. For accurate perception, it must receive the necessary information and make appropriate decisions with faster communication (Boukerche and Sha, 2021; Biswas and Wang, 2023). Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) in South Africa are not yet a full reality, which hinders the full potential of AVs. However, efforts should be made to ensure that in the future, these technologies and applications are relevant and safe for South African conditions.

The data collected through sensors must be fused and processed in real time to generate accurate and timely environmental understanding. The demand for timely data processing and large amounts of data generated hampers cloud computing as they increase the workload on the cloud, causing network delays and, ultimately, leading to insufficient storage (Biswas and Wang, 2023). A News24 (2018) article and Biswas and Wang, (2023) advocate for the need for 5G technologies as a minimum requirement for AVs to function optimally. However, this is a challenging goal in developing countries, and it is a critical matter that must be addressed.

4.3.4 Ethical, Legal, and Societal Considerations

Every technological design that can perceive objects and human beings differently has fundamental ethical considerations. AVs are machines that need to be able to perceive the environment, classifying human beings and objects in the surroundings (Cunneen et al., 2020). AVs face regulatory hurdles. Ethics is key in object and pedestrian detection and recognition, as the vehicle must distinguish a passenger from other vulnerable road users (Szűcs and Hézer, 2022). The introduction of AVs increases risks relating to cybersecurity and privacy, which generate numerous societal, ethical, and legal tensions. The current AV technological limitations present several risks. The critical concern is the inability of the AV perception layer to evaluate scene context and vehicle communication, which also contributes to the greater contextual understanding of AV perception (Cunneen et al., 2020). AV perception is one of the most ethically challenging aspects of AV technology. AV performs tasks such as calculating routes according to predetermined or acquired object values. As such, the actions supported by AV perception are vulnerable to ethical challenges (Cunneen et al., 2020).

AV communication challenges human rights frameworks regarding data ownership and privacy and reinforces the risk of escalating reliance on machine decisions (Cunneen et al., 2020; Su, 2023). The attackers may intercept messages in vehicle communication and raise safety and privacy concerns (Biswas and Wang, 2023). Aligned with this are the ethical challenges of obtaining data based on emerging AV, societal, and commercial connectivity. Far richer AV perception will be possible if the necessary governance regimes are instantiated to support data use in this context (Cunneen et al., 2020). Existing frameworks governing vehicles and transportation will need to be revised for the AV era. Critical policy issues include AV safety validation and testing standards, liability and insurance regimes, data privacy and security, human-machine interface requirements, and maintenance and inspection protocols (Katiyar, Shukla and Chawla, 2024).

Perception deficiencies that give rise to decisional/action gaps that require human driving intelligence to intercede may be identified and investigated. Until AV perception reaches a level of proficiency that matches humans' driving ability without incorporating significant societal, ethical, and legal tensions, AVs will remain dependent upon human intelligence to fill the perception gaps (Cunneen et al., 2020).

The improvement of AVs in the United States and parts of Europe (European Union) is greatly influenced by performing public tests under the strict supervision of a human driver. The involved countries have amended their legislation to allow on-road testing; hence, AVs have significantly improved (Ilková and Ilka, 2017). On the contrary, South Africa faces regulatory hurdles in the development and deployment of AVs (Zhou, 2025). There is a need to strengthen research based on ethical, legal, and societal factors that affect AV technologies and develop legislation and relevant standards to help guide the development, testing, and deployment of AVs in South Africa. A safe and efficient movement of people and goods is a basic constitutional right (Marole et al., 2023).

4.4 The Relationship Between Perception Layer Tasks and Technical Challenges

The primary goal of Chapter 3 was to explain AVs in detail and provide the tasks performed by the AV perception layer to assist in the development of the final guidelines of this study. However, the perception layer tasks (viz. Object Detection and Classification, Lane Detection and Tracking, Real-Time Feedback, Assessment of Potential Obstacles, Sensor Data Fusion, Dynamic Adaptation, Localisation) can be significantly impacted by the aforementioned technical challenges, highlighting the need for robust mitigation strategies:

- The **Object Detection and Classification** task is mainly challenged by environmental conditions, such as *adverse weather conditions* that make it difficult for the perception layer to accurately detect and classify objects (Hasanujjaman, Chowdhury and Jang, 2023; Nahata and Othman, 2023). Additionally, *bad calibration* and *sensor limitations* can also lead to poor detection results. *Ethics* is also a key challenge in object and pedestrian detection and recognition, as the vehicle must distinguish a passenger from other vulnerable road users (Szűcs and Hézer, 2022).
- The **Lane Detection and Tracking** task is also affected by *environmental factors and poor road infrastructure*. Tracking includes real-time tracking achieved by detecting objects consecutively on different frames (Boukerche and Sha, 2021). This suggests that *computational complexities and inadequate processing requirements* may hinder the execution of this task.

- Challenges such as *computational complexities and inadequate processing requirements* hinder the perception layer from successfully performing the **Real-Time Feedback** task. This can lead to delayed decisions and subsequently bad driving behaviours.
- Providing an accurate **Assessment of Potential Obstacles** can be hindered by *adverse weather conditions*, making it difficult for the perception layer to detect obstacles. Consequently, this makes it hard for the perception layer to assess the nature of these obstacles (Boukerche and Sha, 2021; Khatab et al., 2021).
- **Sensor Data Fusion** is primarily challenged by the *incorrect selection of sensors*. Sensors must be complementary and synchronised, as they possess different strengths (Kumar et al., 2022). Additionally, the data collected through sensors must be fused and processed in real time to generate accurate and timely environmental understanding. Therefore, *inadequate processing requirements* can negatively impact data fusion.
- The key to **Dynamic Adaptation** is that the perception layer must continuously update itself and refine perception algorithms and models based on real-world data and feedback from on-road testing (Wang et al., 2020). This task is challenged by *computational complexities and inadequate processing requirements* as it requires more synchronised technologies that enable timely updates.
- **Localisation** accuracy can be compromised by *sensor limitations* and *calibration errors*, leading to incorrect location readings. *Adverse weather conditions* such as snow, fog, and rain present a major challenge for AVs in object detection as they hinder the sensor's ability to capture information about the surroundings, impeding their functionality (Hasanujjaman, Chowdhury and Jang, 2023; Nahata and Othman, 2023). The inability to capture correct information about the surroundings can lead to incorrect location data. AVs perform tasks such as calculating routes according to predetermined or acquired object values. As such, the actions supported by AV perception are vulnerable to *ethical challenges* (Cunneen et al., 2020).

4.5 Related Standards

It being a maturing field, the dearth in standardisation contributes to the challenges presented in section 4.3 above, making it difficult to overcome related complexities; hence, the need for a set of guidelines as envisaged in this study. Three standards are deemed relevant to this study. Two standards are from the International Organization for Standardization (ISO), ISO

26262:2018 and ISO 21448:2019, and one from the British Standard Institute (BSI), PAS 1880:2020.

4.5.1 ISO 26262:2018

The ISO 26262:2018 focuses on functional safety and acknowledges that people and machines make mistakes and things break, which can cause serious accidents. The core aim of the standard is to ensure safety in the event of any failures. However, ISO 26262:2018 lacks an adequate way to incorporate safety issues when linking artificial intelligence (AI) with AVs (Biswas and Wang, 2023). The noticeable gap in ISO 26262:2018 is that it does not consider a subfield of AI, deep learning algorithms, because the standard was published before the boom of AI, leading to the absence of proper ways to standardise the safety issues when incorporating AI for AVs (Liu et al., 2020). The ISO 26262:2018 standard must be revisited to incorporate AI algorithms for AV safety. This study advocates for AI algorithms for accurate AV perception, as discussed in section 4.6.1.

4.5.2 ISO 21449:2019

The ISO 21448:2019 is intended to be applied where proper situational awareness is crucial to safety and where that situational awareness is derived from complex sensors and processing algorithms. It aims to reduce the number of known and unknown unsafe scenarios by identifying triggering events and analysing scenarios and system architecture, and properties. The ISO 21448:2019 standard is intended to be aligned to levels 1 and 2 of the Society of Automotive Engineers (SAE) automation levels. This edition of the standard can be considered for higher levels, but additional measures might be necessary.

4.5.3 PAS 1880:2020

The PAS 1880:2020 standard is intended to support developers of AVs during vehicle trials in which there is a human safety operator who is able to take control of the vehicle (When they are required to do so). It specifies requirements for safety cases for AV trials and development testing in the United Kingdom. This study borrows some of the requirements from this standard.

It is required to prove that AVs are safe with respect to the requirements specified in ISO 26262:2018 (Functional Safety) and ISO 21448:2019 (Safety of Intended Functionality).

Contrary to these requirements, on the other hand, comprehensive safety solutions for the perception systems are still missing (Oboril et al., 2022) – hence, this study contributes by producing a set of guidelines that can guide developers, management, researchers, and standard bodies.

4.6 Approaches to Reduce Perception Errors

Autonomous driving is by no means a single field of technology, but the result of integrating many technologies (Wang, 2021). This section provides some of the current technologies, methods, and industry best practices influencing the perception layer and can potentially be more advanced to assist in reducing perception errors by addressing the aforementioned perception layer challenges.

4.6.1 Artificial Intelligence (AI)

Artificial intelligence (AI) plays a vital role in AV development, and AI-based approaches are utilised for most AV services (Boukerche and Sha, 2021). AVs can use AI applications to detect location and generate actions taken, such as the best routes (Kshetri, 2020). AI is the concept of computer systems imitating human intelligence processes. It is more about teaching machines how to think and learn like humans. AI systems generally absorb enormous volumes of labelled training data, which is used to identify correlations and patterns and use them to forecast future outcomes. Similarly, AVs are expected to perceive the environment and consume a large volume of data to make decisions (Sadaf et al., 2023; Zakaria et al., 2023). AI enables AVs to analyse and interpret data and provide the decision layer with accurate and real-time information. AI's self-learning capabilities help improve its algorithms over time. As a result, it can be used to allow AVs to learn and dynamically adapt over time (Kshetri, 2020).

AVs employ robotics and control theory techniques, such as simultaneous localisation and mapping (SLAM), path planning, obstacle avoidance, and feedback control, to make driving decisions and execute vehicle motion (Katiyar, Shukla and Chawla, 2024). All of these depend on the accuracy of the perceived data. In addition, AVs rely heavily on computer vision algorithms to interpret raw sensor data from various sensors. As with every AI system, AVs need to learn and think using a large amount of data to better understand the environment. This is done through machine learning. Machine learning is a branch of AI that aims to construct and study systems that can learn from data. Machine learning is centred on the goal of developing AVs with cognitive abilities comparable to those of humans (Eraliev et al., 2022). On the other hand, deep learning, as a branch of machine learning, automatically extracts features and patterns from raw data and makes predictions or takes actions based on some rewards (Gupta et al., 2021).

AI techniques, especially deep learning, are pivotal in improving object detection, classification, and decision-making processes in AVs. These algorithms can be trained to recognise South Africa's unique road signs, driving behaviours, and environmental conditions. AI systems can also help with the continuous learning of the AV perception layer. These systems can adapt to new data collected from the diverse South African environment, allowing for better decision-making in real-time (Waymo, 2023b; Katiyar, Shukla and Chawla, 2024). However, while deep learning can achieve impressive accuracy on perception tasks, it lacks the robustness of human perception. As a result, it requires training and testing, allowing it to learn from more data to make more accurate decisions. The testing can be in a simulated or real-world environment, allowing AI models to learn from vast amounts of synthesised data and safely test dangerous or rare scenarios (Katiyar, Shukla and Chawla, 2024).

Special attention must be given to ethical dilemmas in South Africa for both AVs and AI. Some developing countries, such as China, develop AI solutions without giving sufficient consideration to ethical issues (Kshetri, 2020). This may result in building AI solutions that violate privacy laws and human rights (Kshetri, 2020).

4.6.2 Best practices for sensor selection, integration, and error mitigation

4.6.2.1 ***Sensor selection***

One of the major sensor challenges is selecting the right group of sensors and their optimal configuration, which can be used to mimic the human ability to sense and create a reliable picture of the surroundings. During this process, it is important to take note of the different sensors, their advantages, disadvantages, and limitations presented in Table 3.3 in section 3.4.1.1 above (Fayyad et al., 2020). The required perception and prediction rates and accuracy of AV systems can vary depending on the town's complexity. To determine the right group of sensors, AV manufacturers must consider factors such as traffic volume, pedestrian density, traffic signals, road maps, etc. (Hurair, Ju,and Han, 2024). For this reason, in 2022, Tesla removed ultrasonic sensors for most global markets and launched their vision-based occupancy network. Their launch gives longer-range visibility, autopilot high-definition spatial positioning, and the ability to identify and differentiate between objects (Tesla, 2025). Nevertheless, the change led to certain features like auto-parking, summon, and smart summon being limited and inactive. This proves the need for better ways of selecting sensors to fulfil mission tasks.

4.6.2.2 ***Sensor fusion algorithms***

The perception layer of the AV system architecture discussed in section 3.4.1 requires precise and complete data about the environment for AVs to navigate safely, which cannot be obtained solely through one sensor (Realpe, Vintimilla and Vlacic, 2016; Liu et al., 2020). Sensor fusion is at the centre of AV perception. Different sensors, selected as discussed above, are utilised in AVs, and they complement each other to enhance the safety factor of AVs. The different sensors play distinct roles in vehicle perception, with various limitations. Fusing the different sensor data can maximise the effectiveness of different sensors (Wang, 2021). An example of the importance of sensor fusion is that cameras provide details on the texture of objects, while light detection and ranging sensors (LiDARs) provide accurate depth information (Dauptain et al., 2022). Sensor fusion provides a comprehensive view of the environmental data collected from various sensors. It involves methods that combine data and related information into a unified format to enhance the accuracy and reliability of collected data and improve fault tolerance, reducing uncertainty in redundant data measurements (Rosique et al., 2019; Liu et al., 2020). Various constraints exist for different types of sensors in unfavourable weather conditions, as discussed in section 3.4.1.1. Sensor fusion is a robust and precise algorithm that can achieve optimal performance under any weather condition, which can supplant human vision in the AV (Oudeif, Mohsen and Alasry, 2024).

However, efficiently using information from different sensors requires precise synchronisation and calibration of the sensors involved (Dauptain et al., 2022). This approach is crucial for real-time data processing. All sensor acquisitions must be carried out in a synchronised manner and dated on a common time base to guarantee the interpretation of the driving scene (Dauptain et al., 2022). Constructing the perception layer of multi-sensor data fusion and making use of sensor fusion algorithms can provide reliable and effective surrounding environment information to be established during the driving process of autonomous driving vehicles (Wang, 2021). The resulting information from fused sensors is more accurate than it would be when the sensors were used individually.

4.6.2.3 *Sensor Calibration*

Sensor calibration alerts the autonomous system about the sensor's position and orientation. Constant improvement and update of sensors and the sensing system improve the vehicle's perception of its surrounding environment. The sensor system update ensures that the vehicle can accurately identify and understand various objects on the road. The development of this advanced perception layer enables AVs to better adapt to the complex traffic environment and respond accordingly (Su, 2023). In addition to sensor calibration, it is important to maintain vehicle sensors. Maintenance is important throughout the lifecycle of AVs (Kumar et al., 2022). Sensor calibration uses chessboard images for camera calibration to determine the correspondence between the real world and image coordinate systems (Zakaria et al., 2023).

4.6.2.4 *Fault Tolerance*

Fault tolerance is the ability of the system to respond gracefully to unexpected hardware or software failures (Ahangari et al., 2023). It refers to the capability of a system to avoid failures in the presence of faults (Realpe, Vintimilla and Vlacic, 2016). Perception must be reliable in adverse weather, lighting, road conditions, in the presence of sensor uncertainty and noise, and when faced with novel or ambiguous scenes (Katiyar, Shukla and Chawla, 2024). While it is desirable for the perception layer to be fault-free under any conditions, so far, it is hard to guarantee it; hence, there is a need for a fault-tolerant system (Realpe, Vintimilla and Vlacic, 2016; Antonante et al., 2023). A fault-tolerant system ensures the AV perception layer renders the correct system service in the presence of faults to avoid unplanned behaviours and raising safety concerns. In general, implementing fault tolerance implies three steps: error detection, error location, and recovery (Realpe, Vintimilla and Vlacic, 2016).

Fault-tolerant perception for AVs still needs to be further developed to create AVs capable of driving under real road traffic conditions, since on-board vehicle sensors may fail due to bad calibration, erroneous readings, physical or electrical failures, etc., a multi-sensor-based vehicle architecture is a logical response to this issue (Realpe, Vintimilla and Vlacic, 2016).

Realpe, Vintimilla and Vlacic (2016) proposed a federated sensor data fusion architecture to provide fault tolerance to AV perception systems. The proposed architecture minimises the influence of faulty data, allowing the system to enter a tolerated error state, where a recovery action can be performed to avoid failures. In addition, Ondruš et al. (2020) advocate for having backup sensors that could be used in a state where active sensors cannot capture the environment; this could be due to bad weather or unexpected sensor failures.

Fault prevention and fault removal try to avoid the presence of faults. However, this becomes difficult in a complex system. Fault tolerance and fault forecasting strategies both embrace the existence of faults and are focused on keeping the systems operational in the presence of one or more faults.

4.6.3 Edge Computing and 5G

Edge computing aims to handle applications and services with hard real-time requirements, such as in AVs (Hassan, Yau and Wu, 2019; Kwange, Binda and Muronga, 2021). 5G is a cellular network that aspires to achieve substantial improvement in quality of service, such as higher throughput and lower latency (Hassan, Yau and Wu, 2019). The rollout of the 5G network in South Africa supports the high data throughput and low latency required for AVs to communicate with each other and the infrastructure (i.e. v2x communication). This connectivity is vital for real-time decision-making. There are three main characteristics of 5G data: hard real-time data with a strict predefined latency, soft real-time data that can tolerate some defined latency, and non-real-time data that is not time-sensitive (Hassan, Yau and Wu, 2019). On the other hand, edge computing is a technology that enables the evolution of 5G by bringing cloud capabilities near the end users, in order to overcome the intrinsic problems of traditional cloud computing, such as high latency and lack of security. 5G addresses the concern of high latency, whereas edge computing promotes local data processing.

4.6.4 Recommendations for testing and validation of perception systems

Apart from tests under virtual environments or simulations, tests under real driving conditions are essential, in which data on the vehicle status, accidents, traffic, and weather can be collected. This data can be used to train and improve the perception layer, eliminating the challenges of having limited datasets available for AI projects and the available data of questionable quality (Kshetri, 2020; Szűcs and Hézer, 2022). It is important to test AVs in real traffic scenarios because experience is the best teacher, and it helps to optimise the benefits of AVs. The AV technologies tested in real-world conditions adapt to different driving cultures and conditions as they differ across different regions (Waymo, 2023b). Developing a reliable perception layer requires a vast amount of labelled data. In South Africa, there may be limitations in the availability of high-quality, localised datasets that reflect the unique driving conditions and environment. It is key to have regulatory frameworks in place that allow real-world testing to allow AVs to learn from experience without putting people's lives at risk. New learnings and insights from the real world can be gathered during this time to continue refining the technology capabilities and service experience (Waymo, 2023b). Real-world testing will require clear legal frameworks, with safety being a critical consideration. The lack of such frameworks in SA can slow down the deployment of AVs. There is a need for clear regulations tailored to the local environment to prevent perception uncertainties.

4.7 Summary

Table 4.1 provides a summary of the discussion in Chapter 4, drawing attention to the key insights from the chapter. It presents the challenges and describes what each challenge entails, as well as key requirements that can help overcome these challenges.

Table 4.1: A summary of key AV perception challenges and potential requirements

Challenges	Description/ Relevance in this study	Key Requirements	Justification
Sensor limitations	Sensor limitations refer to challenges and failures that occur due to faulty sensors or sensors not meeting the mission requirements.	Sensor selection, Fault tolerance, Sensor calibration, and maintenance	There is a need for effective sensor technologies, which must be correctly chosen to compensate for another sensor's limitations. The sensor system must be fault-tolerant.
Environmental factors	The focus is on how to enable vehicles to cope with them	Sensor cleaning strategies, Artificial Intelligence, Advanced sensor fusion algorithms, Sensor calibration and maintenance, Testing and validation	As it is difficult to deal with adverse weather conditions, there must be a way to clean sensors and maintain sensor quality. For clear

			perception, there is a need for more advanced and robust sensor fusion algorithms as well as
Road infrastructures	The road infrastructure challenge is beyond the scope of this study. However, it must be noted that it also affects autonomous vehicles and causes perception errors.		
Computational complexities and Processing requirements	A key aspect that affects AV perception is faster communication and real-time data processing	Artificial Intelligence, 5G, and edge computing integration	Integrating 5G technologies and edge computing enables faster communication and data processing by bringing processing requirements (edge processing and storage) closer to where the data is generated.
Ethical, legal, and societal considerations	These challenges may not directly affect the developers and engineers of AVs. However, they must disclose the AV requirements to relevant stakeholders, and it is also their task to ensure AVs abide	Development of Standards, regulations, or new laws	AV developers and manufacturers need to incorporate ethical, legal, and societal aspects in AVs tailored to the local environment

	by the ethical standards.		

Chapter 5: Proposed Guidelines

5.1 Introduction

This chapter explains how the guidelines, as an artefact of this study, were developed and further presents a set of preliminary guidelines developed from insights provided in Chapters 3 and 4. It further explains the correlation between the insights drawn from Chapters 3 and 4. This chapter is guided by RSQ3:

RSQ3: What guidelines could be followed to reduce perception errors in the Autonomous Vehicle System Architecture?

5.2 Guideline Formulation

The artefact of this study is a method presented in the form of guidelines as stated in section 2.5.2. Various types of guidelines exist, including golden rules, heuristics, principles, general guidelines, rules, and standards. These types of guidelines vary in terms of authority and generality (Cowley, 2009). The guidelines of interest in this study are general guidelines and more technology-oriented (Dix et al., 2004). Guidelines are generally rooted in theory, which may be supported by empirical evidence or based on good practice (Pisanelli, Gangemi and Steve, 2000; Cowley, 2009).

In the context of this study, the initial guidelines stem from literature and relevant standards. Chapter 3 presented tasks that are performed by the perception layer to guide the development of the guidelines to cater to the associated tasks. Chapter 4 reflected on the challenges encountered in the development and full deployment of autonomous vehicles (AVs) and strategies that can help overcome them. Chapter 4 further identified key requirements that inform the development of guidelines. The study ensures that the initial guidelines of this study enhance and complement the well-established guidelines in the automotive industry and safety standards. The guidelines presented in Table 5.1 were constructed and described in terms of the properties below, adapted from (Dix et al., 2004; Leavitt and Shneiderman, 2006; Cowley, 2009) studies.

Properties used to describe guidelines:

1. **Design Context:**

Type of design problem to which the guidelines can be applied

2. **Title:**

   A single textual natural language sentence that is expressed as an instruction or suggestion (Cowley, 2009)

3. **Description:**

   It may be referred to as content (Cowley, 2009) or comments (Leavitt and Shneiderman, 2006). In this study, it is referred to as a description, as it provides the information embodied in the guideline (Cowley, 2009). It provides an interpretation of the title.

4. **Rationale:**

   Rationale refers to the relevance and importance behind the guideline. Kotzé, Renaud and Biljon (2008) argues that a guideline does not include its rationale; however, this study argues for its necessity. General guidelines may conflict with each other when applied; as such, it is important to understand their theoretical foundation and importance (Cowley, 2009).

5. **References:**

   Referred to as sources by Leavitt and Shneiderman (2006) and as the origin by Cowley (2009) provides evidence of scientific or practical credibility, which may be supported by empirical evidence. Guidelines are generally rooted in theory and can be grounded purely in good practice (Cowley, 2009).

6. **Level of Authority:**

   Refers to an indication of whether the guideline is crucial to be followed or can be considered less crucial. An indication of the authority of the guidelines in Table 5.1 is represented using a five-point "Strength of Evidence" rating. The ratings were compiled by experts to give them credibility (Leavitt and Shneiderman, 2006; Cowley, 2009).

5.3 Preliminary Guidelines

5.3.1 Objective

These guidelines aim to improve perception capabilities by minimising perception errors in autonomous vehicles to improve overall AV safety.

5.3.2 Design Context

Perception errors hinder the successful deployment of any sensor-based system. These guidelines aim to be applied to the design and development of the AV perception layer. The application of these guidelines aligns with relevant safety standards such as ISO 26262:2018 and PD ISO/PAS 21448:2019.

Table 5.1: Preliminary Guidelines

GUIDELINE 1 (SENSOR FUSION): ESTABLISH ALGORITHMS FOR SENSOR FUSION IN AV PERCEPTION					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Develop and implement more advanced, robust, and precise sensor fusion algorithms that combine the large amount of data generated by individual sensors and related information in a unified format. The algorithms must synchronise all sensor data acquisitions based on a common timestamp to guarantee accurate interpretations.					
Rationale: The sensor fusion algorithms leverage the strengths of different sensors to overcome the limitations of individual sensors and enhance perception accuracy. The algorithms improve accuracy, reliability, and fault tolerance and decrease uncertainty in redundant data measurements. The integration of sensors could help address the challenge of object and lane detection in adverse weather conditions by providing a clear picture of the environment from different angles.					
References: Realpe, Vintimilla and Vlacic, 2016; Van Brummelen et al., 2018; Rosique et al., 2019; PAS 1880:2020; Wang, 2021; Dauptain et al., 2022; Hasanujjaman, Chowdhury and Jang, 2023; Nahata and Othman, 2023; Oudeif, Mohsen and Alasry, 2024					
GUIDELINE 2 (SENSOR CALIBRATION AND MAINTENANCE): REGULARLY CALIBRATE AND MAINTAIN THE VEHICLE SENSORS					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Constantly improve and update sensors to help reduce errors caused by sensor drift and degradation. Develop sensor cleaning strategies to cope with adverse weather conditions.					
Rationale: Sensor calibration and maintenance requirements are crucial for sensor fusion and implementing algorithms for obstacle detection, localisation, and mapping. Regular maintenance and updates may help to address any potential issues and keep the perception system up to date.					
References: ISO/PAS 21448:2019; Yeong et al., 2021; Dauptain et al., 2022; Kumar et al., 2022; Su, 2023					

GUIDELINE 3 (FAULT TOLERANCE): ENSURE THE PERCEPTION SYSTEM IS ABLE TO RECOVER FROM ERRORS					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Additional sensor coverage should be considered to ensure safe and secure AV operations. This can be achieved by installing additional sensors. The implementation of a fault-tolerant system must be able to detect the error, discover the error location, and recover from the detected error.					
Rationale: The degradation or loss of a single sensor can make it necessary to bring the vehicle to a stop or cause safety issues. It is necessary to have measures in place for AVs to learn to operate in the presence of faults to avoid unplanned behaviours, especially those resulting from sensor faults.					
References: Realpe, Vintimilla and Vlacic, 2016; Pas 1880:2020; Zhao et al., 2024					
GUIDELINE 4 (REAL-TIME DATA PROCESSING): ENSURE ROBUST V2X COMMUNICATION					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Integrate edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing, as the integration offers more advantages. The large amount of data collected through sensors and communication networks may increase the workload on the cloud and network delays, which hamper cloud computing and pose damage to the system.					
Rationale: Edge computing caters for applications with wireless communication requirements. It stores and processes massive amounts of data where it is generated to overcome any possible network delays. 5G supports highly interactive applications that are computationally intensive and have high quality of service (QoS) requirements.					
References: Hassan, Yau and Wu, 2019; Sittón-Candanedo et al., 2019; Biswas and Wang, 2023; Pandharipande et al., 2023; Trapani and Longo, 2023					
GUIDELINE 5 (LEGAL, AND MORAL CONSIDERATION): ADDRESS ETHICAL, LEGAL, AND SOCIETAL ISSUES					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Strengthen research on ethical, legal, and societal issues for the improvement of safety and reliability. Engage with ethicists, legal experts, and policymakers to develop relevant standards and legislation to address ethical and legal issues tailored to the South African region. The standards and legislation must account for real-world testing and AV deployment, and development. These ethical, legal, and societal considerations must be incorporated into the design of the AV perception layer.					
Rationale:					

AVs require a predetermined way of dealing with specific ethical, legal, and societal issues. The standards will mainly help in making control decisions. However, AVs need ethical guidance on their interaction and communication with other vehicles and pedestrians.
References: Martínez-Díaz and Soriguera, 2018; Szűcs and Hézer, 2022; Su, 2023

GUIDELINE 6 (TESTING AND VALIDATION): DEVELOP AND TEST PERCEPTION ALGORITHMS UNDER CONDITIONS VERY CLOSE TO REALITY					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Rigorously test perception algorithms in real-world conditions or conditions that are very close to reality, as they enable the vehicle to learn more about different environments and scenarios. Precautionary measures must be taken to ensure human safety. Advanced algorithms must be used for environment mapping, and redundant systems must be employed to cross-verify environmental data.					
Rationale: Extensive testing can help identify potential perception errors and refine the system's performance. Real-world testing, visual testing, simulation, and validation against ground truth data can help identify and reduce the risks of perception errors.					
References: ISO 26262:2018; Rosique et al., 2019; Szűcs and Hézer, 2022; Pandharipande et al., 2023; Piazzoni et al., 2023					

GUIDELINE 7 (ARTIFICIAL INTELLIGENCE): UTILISE ARTIFICIAL INTELLIGENCE ALGORITHMS IN COMPLIANCE WITH SAFETY STANDARDS					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Train AI algorithms to recognise South Africa's unique road signs, environmental conditions, and driving behaviours. Artificial intelligence algorithms must comply with relevant safety standards and legislation. The data used in such algorithms must be accurate and representative of the real world. Use AI algorithms to support all other requirements (Guidelines 1-6).					
Rationale: The use of AI systems, such as machine learning and deep learning, in AV perception can help the system to learn and improve over time.					
References: ISO 26262:2018; Betz et al., 2019; ISO/PAS 21448:2019; Rosique et al., 2019; Fayyad et al., 2020; Yurtsever et al., 2020; Pas 1880:2020; Bachute and Subhedar, 2021; Biswas and Wang, 2023; Nahata and Othman, 2023; Sanjay and Yashwanth, 2023; Zakaria et al., 2023; Hurair, Ju and Han, 2024					

5.4 Relationship between Guidelines, Perception Layer Tasks, Challenges and Technical Enablers

The guidelines presented in section 5.3 are not arbitrary but rather a logical consequence of the interplay between the perception tasks presented in section 3.5, the technical enablers available to perform these tasks (presented in section 4.6), and the challenges that hinder the development of a robust perception layer presented in section 4.3. The outlined roles are Object Detection and Classification, Lane Detection and Tracking, Real-Time Feedback, Assess Potential Obstacles, Sensor Data Fusion, Dynamic Adaptation, and Localisation. Technical enablers include Artificial Intelligence, Sensor Selection, Sensor Fusion Algorithms, Sensor Calibration, Fault Tolerance, Edge Computing and 5G, and Testing and Validation. Challenges that impede accurate perception include sensor limitations and failures, environmental factors and road infrastructures, computational complexities and processing requirements, and ethical, legal and societal considerations.

The guidelines in section 5.3 aim to reduce perception errors, emerging as an approach to leverage the existing technical enablers to mitigate the challenges and enable the reliable performance of the perception tasks. As an example, the challenge of inadequate processing requirements can be mitigated by employing the combination of Edge Computing and 5G for faster data processing, improving the Real-Time Feedback task. From this emerges guideline 4 (Real-Time Data Processing), aiming to ensure robust V2X communication by integrating edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing.

This example reinforces the notion that these guidelines were not arbitrary but rather were systematically derived through a comprehensive exploration and resolution of RSQ 1 and RSQ 2, and their correlation as established in section 4.4 and Table 4.1. The relationship between the guidelines, perception layer tasks, challenges, and technical enablers is summarised in Table 5.2 below.

Table 5.2: The relationship between the guidelines, perception layer tasks, challenges, and technical enablers

Guideline (No. & Title)	Primary Perception Tasks Supported	Main Challenges Addressed	Key Technical Enablers / Requirements
G1. Sensor Fusion	Object detection & classification; lane detection & tracking; assessment of obstacles; localisation; sensor data fusion	Sensor limitations & failures; adverse weather conditions	Advanced multi-sensor fusion algorithms; common time-base synchronisation; tight calibration across sensors
G2. Sensor Calibration & Maintenance	Object detection & classification; lane detection & tracking; localisation; dynamic adaptation; obstacle assessment	Sensor drift/degradation, mis-calibration; adverse weather conditions	Regurlar calibration procedures; self-cleaning strategies (e.g., wipers, air puffers); lifecycle maintenance
G3. Fault Tolerance	Robust execution of all perception tasks.	Adverse weather; lighting, road conditions; sensor uncertainty and noise; sensor limitations, and failures	Fault-tolerant system
G4. Real-Time Data Processing & V2X	Real-time feedback; supports lane tracking and dynamic adaptation via timely updates	Computational complexity; processing/latency constraints; limited V2X infrastructure causing delays	Edge computing near data sources; 5G for low-latency/high throughput; robust real-time processing pipelines
G5. Ethical, Legal & Societal Considerations	Object detection and classification; localization; Real-time feedback	AVs face ethical, legal, societal, and regulatory hurdles, primarily due to their involvement in acquiring data vulnerable to cybersecurity and privacy risks.	Alignment with ISO 26262 & ISO 21448; development of tailored standards/policies; trial safety cases (e.g., PAS 1880)
G6. Testing & Validation	All perception tasks	Dataset scarcity/quality; unknown unsafe scenarios; need for empirical validation to reduce perception errors	On-road trials under controlled safety; simulation and ground-truth validation; redundancy for cross-verification
G7. Artificial Intelligence (AI)	Object detection & classification; dynamic adaptation; Real-time feedback	computational complexities; inadequate processing	ML/DL models trained on local conditions (signs, behaviour, weather); simulation to expose rare/dangerous scenarios; compliance with safety standards

5.5 Summary

This chapter explains what guidelines are and how they were formulated. This study adapted the guideline formulation methods from extant literature in this field of study. The chapter discussed six properties used to describe a guideline: Design Context, Title, Description, Rationale, References, and the Level of Authority. Finally, the chapter provided the seven (7) preliminary guidelines developed from insights provided in Chapters 3 & 4. The key requirements from the guidelines are Sensor Fusion, Sensor Calibration and Maintenance, Fault Tolerance, Real-Time Data Processing, Legal and Moral Considerations, Testing and Validation, and Artificial Intelligence. This chapter discussed the link between the perception tasks, the technical enablers available to perform these tasks, and the challenges that hinder the development of a robust perception layer.

Chapter 6: Evaluation of Initial Guidelines

6.1 Introduction

Evaluation plays a critical role in design science research (DSR). This chapter presents the evaluation approach used and the findings from the online questionnaire used as the data collection method in this study (See section 2.9 for a detailed discussion on the data collection method). The online questionnaire was administered to ten participants to assess the rigour and effectiveness of the preliminary guidelines. Furthermore, this chapter provides demographics of the expert participants. The evaluation results address the research sub-questions. The findings employ descriptive statistical analysis to visualise and understand the patterns in the collected data.

6.2 Process of Conducting Evaluation

To evaluate preliminary guidelines, this study utilised the four-step process proposed by Venable, Pries-Heje and Baskerville (2016) to inform the decision of choosing the best evaluation strategy. These steps are discussed as follows:

Step 1: Explicate the goals of the evaluation

DSR evaluation has four possible goals: Rigour, Uncertainty and risk reduction, Ethics, and Efficiency (Venable, Pries-Heje and Baskerville, 2016). This study considered rigour as a means to ensure that the proposed guidelines are appropriate in reducing perception errors in autonomous vehicles (AVs). This objective was achieved by evaluating the effectiveness of the guidelines via an ex-post naturalistic evaluation see Table 6.1.

Step 2: Choose the evaluation strategy

Figure 6.1 below presents evaluation strategies and selection criteria. Based on the needs of a project, a range of strategies can be pursued: Purely Technical, Technical Risk & Efficacy, Quick & Simple, and Human Risk & Effectiveness (Venable, Pries-Heje and Baskerville, 2016). The Human Risk and Effectiveness strategy was considered appropriate in this study for evaluating the guidelines for reducing perception errors in AVs. The motivation for selecting the Human Risk and Effectiveness strategy is the need to rigorously establish that the utility/benefit of the guidelines in the design and development of the perception layer of AVs will continue in real situations and over the long run, despite the complications of human and social difficulties of adoption and use. As stated in Figure 6.1 below, a Quick & Simple strategy is more suitable for projects where the utility of the artefact has low social and technical risks. Furthermore, a Technical Risk & Efficacy is required if the major design risk is purely technical, and where it may be costly, either money or safety implications, to evaluate the artefact with real people and real systems in a real setting (Venable, Pries-Heje and Baskerville, 2016). This study does not employ either of the two strategies as there are social and user-oriented risks that must be considered in the design of the artefact and subsequent use, and it requires the real users in a real setting for evaluation (Venable, Pries-Heje and Baskerville, 2016). The last strategy, Purely Technical Artefact, is unsuitable for this study as it is most applicable when the artefact is purely technical and does not consider any social aspect (Venable, Pries-Heje and Baskerville, 2016).

DSR evaluation strategies	*Circumstance selection criteria*
Quick & Simple	If small and simple construction of design, with low social and technical risk and uncertainty
Human Risk & Effectiveness	If the major design risk is social or user oriented *and/or* If it is relatively cheap to evaluate with real users in their real context *and/or* If a critical goal of the evaluation is to rigorously establish that the utility/benefit will continue in real situations and over the long run
Technical Risk & Efficacy	If the major design risk is technically oriented *and/or* If it is prohibitively expensive to evaluate with real users and real systems in the real setting and/or If a critical goal of the evaluation is to rigorously establish that the utility/benefit is due to the artefact, not something else
Purely Technical Artefact	If artefact is purely technical (no social aspects) or artefact use will be well in future and not today

Figure 6.1: Evaluation strategy selection criteria (adapted from Venable, Pries-Heje and Baskerville, 2016)

Step 3: Determine the properties to evaluate

The guidelines were evaluated through a naturalistic evaluation to determine whether the guidelines are relevant and essential in reducing perception errors in AVs. Additionally, it was important to determine whether they should be applied in the design and development of AVs.

Step 4: Design the individual evaluation episode(s)

Following the preceding steps, the evaluation process included ten participants who were administered an online questionnaire with questions based on the properties in step 3.

6.3 Evaluation Approach

The primary purpose of DSR evaluations is to rigorously demonstrate the utility of the artefact being evaluated and how well it may perform. DSR evaluation in this study aims to determine whether and how well the developed evaluand (guidelines) achieves its purpose. To achieve this, the study follows the Framework of Evaluation in Design Science (FEDS) proposed by (Venable, Pries-Heje and Baskerville, 2012) as presented in Table 6.1, to assist in evaluating the preliminary guidelines formulated in this study. An ex-post naturalistic evaluation approach was conducted to evaluate these guidelines.

An ex-post naturalistic approach explores the performance of a solution and assesses the extent to which it solves the problems in a real-world environment (Venable, Pries-Heje and Baskerville, 2012). As can be observed from Table 6.1 below, this study adopted a case study approach focusing on South Africa as a unit of analysis. Furthermore, the participants completed an online questionnaire to evaluate the preliminary guidelines. The overarching aim of this evaluation was to determine the relevance and rigour of the proposed guidelines.

Table 6.1: Design science research evaluation framework (adapted from Venable, Pries-Heje and Baskerville, 2012)

DSR Evaluation Method Selection Framework	Ex Ante	Ex Post
Naturalistic	- Action Research - Focus Group	- Action Research - **Case Study** - Focus Group - Participant Observation - Ethnography - Phenomenology - Survey (qualitative or quantitative)

Artificial	- Mathematical or Logical Proof - Criteria-Based Evaluation Lab Experiment - Computer Simulation	- Mathematical or Logical Proof - Lab Experiment - Role Playing Simulation - Computer Simulation - Field Experiment

6.4 Research Participants

According to Lopez and Whitehead (2013), it is sufficient for eight to fifteen participants to provide adequate information during the data collection process. The participants of this study consisted of ten professionals with extensive experience in the automotive industry and knowledge of AVs, in particular. Among the ten experts, two were from a multinational South African automotive manufacturer, Company 2. A pragmatic approach was taken to use an online platform, Prolific, to secure the remaining eight participants. The use of Prolific yielded eight additional responses from a diverse pool of participants across South Africa, Hungary, the United Kingdom, and the United States. Consequently, the three participants from other countries provided an invaluable global perspective. Their validation and critique of the guidelines showed the relevance of the artefact, not only to the South African context but in a generalised manner to similar countries as South Africa.

Participant Selection Criteria on Prolific

The criteria on Prolific to select participants were that the participants worked within the automotive industry across all countries. The participants should all have been active in the past 90 days at the time data was collected and participated in similar studies within that period.

From the participants of the study, 70% resided in South Africa (SA) and worked within the SA automotive industry, while the remaining 30% resided in Hungary, the United Kingdom, and the United States, respectively. However, the 30% residing in developed countries helped to evaluate the guidelines of this study using their general knowledge of AVs. 50% of the participants were males, 30% were females, and 20% preferred not to reveal their gender. All participants worked within the automotive sector, 80% of whom are full-time employees, and 20% are part-time employees. Additionally, the ethnic composition of the participants was as follows: 20% identified as Asian, 40% as Black, and 20% as White. A further 20% of participants opted not to disclose their ethnicity.

A summary of the experts' demographic information is presented in Table 6.2 below

Table 6.2: Participant demographical information summary

Participant	Gender	Country of residence	Employment status	Ethnicity	Industry
Participant 1	Unknown	South Africa	Full-Time	Unknown	Automotive
Participant 2	Unknown	South Africa	Full-Time	Unknown	
Participant 3	Female	South Africa	Part-Time	Black	
Participant 4	Male	South Africa	Part-Time	Asian	
Participant 5	Female	South Africa	Full-Time	Black	
Participant 6	Female	South Africa	Full-Time	Asian	
Participant 7	Male	Hungary	Full-Time	White	
Participant 8	Male	South Africa	Full-Time	Black	
Participant 9	Male	United States	Full-Time	White	
Participant 10	Male	United Kingdom	Full-Time	Black	

6.5 Data Collection Findings

A description of each guideline was provided, and the experts were requested to assess the guidelines based on the perception layer tasks using a Likert scale. The questionnaire also allowed the experts to provide detailed comments to support their ratings.

6.5.1 Autonomous Vehicles Perception Tasks

This section of the questionnaire was guided by research sub-question 1:

RSQ1: What should be the key tasks of the perception layer of the Autonomous Vehicles System Architecture?

As the study aimed at developing guidelines to reduce perception errors, it was crucial to outline and understand the key tasks of the perception layer in the Autonomous Vehicle System Architecture (AVSA). These tasks were presented to experts for validation and critique. The experts were asked to rate the importance of the AV perception layer tasks based on their knowledge. The experts used a Likert Scale to determine if the tasks were: Not important (1); Not so important (2); Somewhat important (3); Very important (4); Extremely important (5).

Figure 6.2 shows the identified perception tasks and participants' responses. The responses show that all the tasks are important. These results are further discussed below:

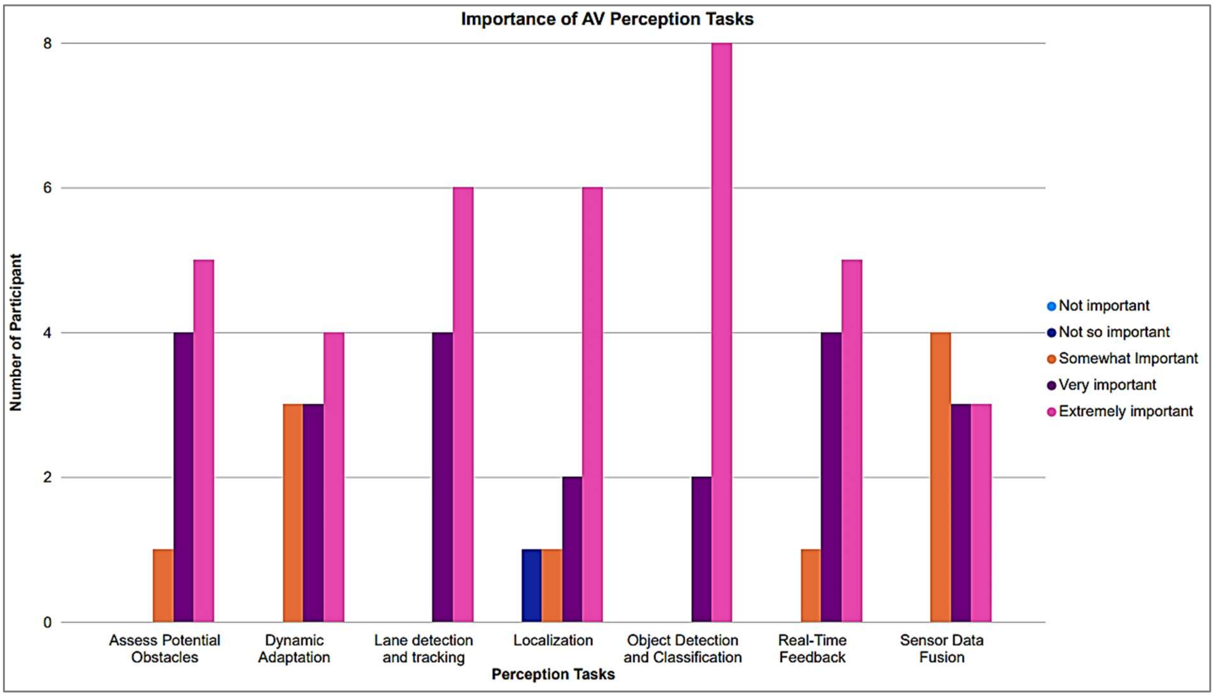

Figure 6.2: Autonomous Vehicles Perception Tasks Results

- ***Assess Potential Obstacles***

  Assessing potential obstacles is defined as the evaluation and comprehensive understanding of the nature and depth of any obstacles that can hinder AV perception and overall functionality, ensuring the safety of AVs (Ondruš et al., 2020). The data presented in Figure 6.2 indicates that 50% of the participants rated the task as 'extremely important', with an additional 40% considering it 'very important', and only 10% rated it as 'somewhat important'. None of the participants rated the task as 'not so important' or 'not important', suggesting that the ability to assess potential obstacles is viewed as a critical task.

- ***Dynamic Adaptation***

  Dynamic adaptation refers to the ability of the perception layer to continuously update and refine perception algorithms and models based on real-world data and feedback from on-road testing (Wang et al., 2020). According to the results in Figure 6.2, 40% of the participants considered the task 'extremely important', whereas 30% rated it as 'very important'.

A further 30% of participants rated the task as ‘somewhat important’. Notably, no participants rated dynamic adaptation as ‘not so important’ or ‘not important’, suggesting that the 30% rated it ‘somewhat important’ may not necessarily consider it essential, but acknowledge that it still holds a degree of significance. Consequently, the absence of ratings in the lowest categories reinforces an overall high-level agreement on the task’s importance.

- ***Lane Detection and Tracking***

Lane detection and tracking ensure that vehicles stay in their assigned lane and avoid collisions with vehicles in adjacent lanes (Zakaria et al., 2023). The results in Figure 6.2 show that 60% of the participants rated the task as ‘extremely important’, whereas 40% considered it ‘very important’. The results indicate that the lane detection and tracking task is crucial for AV perception. None of the experts rated the task as ‘not so important’, ‘not important’ suggesting that it is viewed as a critical task.

- ***Localisation***

Localisation refers to the accurate determination of the vehicle's exact position to know where the AV is in the scene (Bachute and Subhedar, 2021). Based on the results, 60% of the participants considered localisation as ‘extremely important’, with a further 20% rating it ‘very important’ and 10% as ‘somewhat important’. However, a minority of 10% expressed a dissenting opinion, rating localisation as ‘not so important’. While a significant majority (80%) of participants acknowledged the importance of accurate localisation, the 10% with a dissenting opinion indicates mixed views on its absolute criticality for AV perception.

- ***Object Detection and Classification***

Object detection and classification refer to the ability of AVs to recognise and classify objects in the environment based on their characteristics and behaviours (Wang et al., 2020). The results in Figure 6.2 show that 80% of the participants rated the task as ‘extremely important’, whereas 20% considered it ‘very important’. The results indicate a clear agreement that the object detection and classification task is critical in AV perception as none of the experts rated the task as ‘not so important’ or ‘not important’.

- ***Real-Time Feedback***

  Real-time feedback, defined as the perception layer's ability to transmit immediate and accurate environmental insights to the decision layer (Betz et al., 2019). The data presented in Figure 6.2 reveals that 50% of the participants rated this task as 'extremely important', with an additional 40% considering it 'very important', and only 10% rated it as 'somewhat important'. Similar to assessing potential obstacles, real-time feedback is also viewed as a critical task, as there are no participants who rated it as 'not so important' or 'not important'.

- ***Sensor Data Fusion***

  Sensor data fusion is about gathering data from various sensors to provide a comprehensive view of the environment (Ondruš et al., 2020; Wang et al., 2020). The results in Figure 6.2 show that 30% of the participants rated the task as 'extremely important', 30% as 'very important', and a notable 40% considered the task as 'somewhat important'. These results show that there is a moderate agreement on its importance but less certainty about it being a crucial task in AV perception. Importantly, no participant rated sensor data fusion as 'not important' or 'not so important'. This data shows that sensor data fusion is recognised as a necessary component of AV perception.

The overall results indicate that *object detection and classification*, and *lane detection and tracking* are the most important tasks of the perception layer. Followed by *assessing potential obstacles* and *real-time feedback*. Participant 1 noted, "*Object detection and, more importantly, the correct classification and level of danger is one of the cornerstones of the AV systems*", to cement the importance of *object detection and classification* as well as *assessing potential obstacles*.

6.5.2 Guidelines

This section of the questionnaire was intended to collect data that relates to research sub-questions 2 and 3:

RSQ2: What are the technical enablers and challenges encountered in autonomous vehicles?

RSQ3: What guidelines could be followed to reduce perception errors in the Autonomous Vehicle System Architecture?

The guidelines presented and discussed in Chapter 5 were evaluated in this section of the questionnaire to inform the final set of guidelines. To review and validate these guidelines, experts were provided with a brief background of each guideline and were asked to answer questions on the following seven areas:

- The Guideline Relevance in Improving Autonomous Vehicle Perception
- The Importance of the Guideline for Autonomous Vehicle Perception Layer Development
- The Guideline Addresses Various Factors Contributing to Perception Errors
- The Significant Impact of the Guideline on Improving Perception Accuracy and Reliability
- The Necessity of Applying the Guideline in Perception Layer Design:
- The Implementation Difficulty of the Guideline in Autonomous Vehicle Perception Layer Development
- The Negative Impact of Failing to Incorporate the Guideline on Autonomous Vehicle Perception Accuracy and Reliability

To respond to the questions, experts used a Likert scale to determine if they: Strongly Disagree (1); Disagree (2); Neutral (3); Agree (4); Strongly Agree (5), with the guideline. The results are presented below. It is worth noting that only nine participants responded to this section of the questionnaire, as one participant chose to skip this section, and the response is recorded as 'no response'.

6.5.2.1 ***Guideline 1 (Sensor Fusion)***

Guideline 1 pertains to establishing robust sensor fusion algorithms that combine the data generated by individual sensors into a comprehensive view. Participants evaluated Guideline 1 using the criteria presented above, and the results are shown in Figure 6.3.

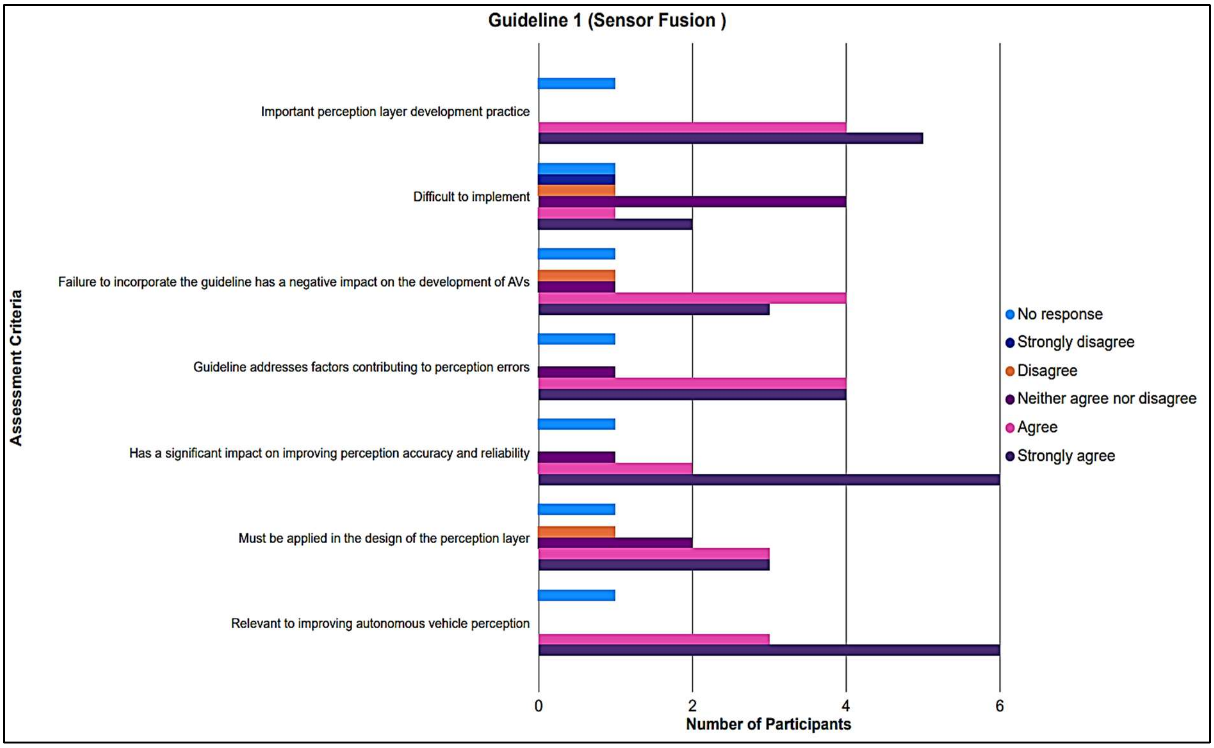

Figure 6.3: Guideline 1 Evaluation Results

Guideline Relevance in Improving Autonomous Vehicle Perception:

The data depicted in Figure 6.3 demonstrates a strong affirmation among participants regarding the relevance of guideline 1 (sensor fusion) in improving AV perception. Specifically, 60% of participants strongly agreed on its relevance, while 30% agreed. Consequently, the data indicate that guideline 1 (sensor fusion) is relevant for enhancing AV perception capabilities.

Importance of the Guideline for Autonomous Vehicle Perception Layer Development:

As illustrated in Figure 6.3, participants evaluated the importance of guideline 1 (sensor fusion) within the context of AV perception layer development. A significant 50% of participants strongly agreed on its importance, while 40% agreed. This indicates a consensus among participants that guideline 1 (sensor fusion) is an important AV perception layer practice, reinforcing the aforementioned findings concerning its relevance.

Guideline Address Factors Contributing to Perception Errors:

Analysis of the data presented in Figure 6.3 reveals a considerable proportion of participants believe that guideline 1 (sensor fusion) effectively addresses various factors contributing to perception errors, with 40% strongly agreeing and 40% agreeing. Furthermore, 10% of the participants indicated that they ‘neither agree nor disagree’.

Significant Impact of the Guideline on Improving Perception Accuracy and Reliability:

The results depicted in Figure 6.3 indicate that 60% of the participants strongly agreed on the significance of guideline 1 (sensor fusion) in the development of AV perception and its subsequent role in improving perception accuracy and reliability, while an additional 20% agreed. The remaining 10% expressed a neutral opinion (neither agreed nor disagreed).

Necessity of Applying the Guideline in Perception Layer Design:

The data presented in Figure 6.3 further illustrate that 30% of participants strongly agreed that guideline 1 (sensor fusion) must be applied in the design of the perception layer, with an additional 30% agreeing. However, a notable 20% of participants neither agreed nor disagreed, and 10% indicated disagreement.

Implementation Difficulty of the Guideline in Autonomous Vehicle Perception Layer Development:

Participants evaluated the difficulty of implementing guideline 1 (sensor fusion) when developing the AV perception layer. The results illustrated in Figure 6.3 revealed that 20% of the participants strongly agreed with the implementation difficulty, whereas an additional 10% agreed. A substantial 40% of the participants neither agreed nor disagreed. Conversely, 10% disagreed, and a further 10% strongly disagreed.

Negative Impact of Failing to Incorporate the Guideline on Autonomous Vehicle Perception Accuracy and Reliability:

The results presented in Figure 6.3 suggest a considerable concern among participants regarding the potential negative consequences of neglecting Guideline 1 (sensor fusion) on AV perception accuracy and reliability. The results revealed that 30% of the participants strongly agreed that the absence of guideline 1 (sensor fusion) can negatively impact AV perception, while 40% agreed. An additional 10% of participants remained neutral (neither agreed nor disagreed), and 10% indicated disagreement.

6.5.2.2 ***Guideline 2 (Sensor Calibration and Maintenance)***

Guideline 2 is primarily about regular calibration and maintenance of AV sensors. Participants evaluated Guideline 2 using the criteria presented above, and the results are shown in Figure 6.4.

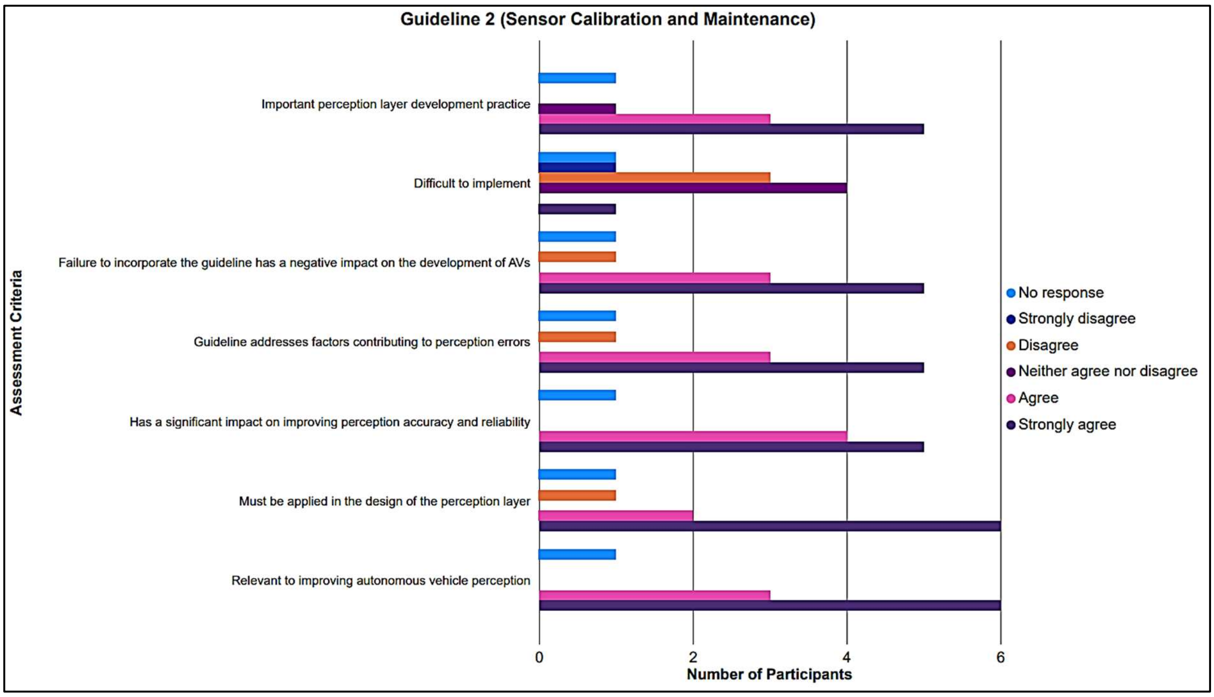

Figure 6.4: Guideline 2 Evaluation Results

Guideline Relevance in Improving Autonomous Vehicle Perception:

Figure 6.4 presents results on the relevance of guideline 2 (sensor Calibration and Maintenance) in improving AV perception capabilities. The data indicates a strong consensus among participants, with 60% strongly agreeing and an additional 30% agreeing with its relevance. The results further reveal that no participant rated the guideline as ‘neither agree nor disagree’, ‘disagree’, or ‘strongly disagree’.

Importance of the Guideline for Autonomous Vehicle Perception Layer Development:

The data presented in Figure 6.4 demonstrate that 50% of the participants strongly agreed that guideline 2 (sensor Calibration and Maintenance) is an important AV perception layer development practice, while an additional 30% agreed. Furthermore, 10% of the participants expressed a neutral stance, while no participants disputed (disagreed or strongly disagreed) its importance.

Guideline Address Factors Contributing to Perception Errors:

Participants evaluated the effectiveness of guideline 2 (sensor Calibration and Maintenance) in addressing factors contributing to perception errors. The results depicted in Figure 6.4 indicate that most participants expressed positive agreement, with 50% strongly agreeing and 30% agreeing. However, an additional 10% of the participants disagreed.

Significant Impact of the Guideline on Improving Perception Accuracy and Reliability:

The findings illustrated in Figure 6.4 demonstrate a strong consensus among participants concerning the significant impact of guideline 2 (sensor Calibration and Maintenance) in the development of AV perception and its role in improving accuracy and reliability. A considerable proportion of participants expressed a positive agreement, with 50% strongly agreeing and 40% agreeing. Remarkably, no participants took a neutral stance (neither agreed nor disagreed) or disagreed with guideline 2.

Necessity of Applying the Guideline in Perception Layer Design:

The results presented in Figure 6.4 reveal that 60% of participants strongly agreed and 20% agreed that guideline 2 (sensor Calibration and Maintenance) must be applied in the design and development of the AV perception layer to minimise perception errors and improve perception accuracy. However, 10% of the participants disagreed with the guideline.

Implementation Difficulty of the Guideline in Autonomous Vehicle Perception Layer Development:

Figure 6.4 illustrates that only 10% of participants strongly agreed that guideline 2 (sensor Calibration and Maintenance) is difficult to implement in the development of the AV perception layer. Furthermore, a considerable 40% neither agreed nor disagreed, expressing neutrality. However, 30% of participants disagreed, with an additional 10% strongly disagreeing, suggesting that the guideline is not difficult to implement.

Negative Impact of Failing to Incorporate the Guideline on Autonomous Vehicle Perception Accuracy and Reliability:

The data presented in Figure 6.4 depicts that a strong majority of participants (50% strongly agreed, 30% agreed) believe that it is crucial to incorporate guideline 2 in the AV perception layer development and failure to do so would negatively impact perception accuracy and reliability. On the contrary, only 10% expressed disagreement.

6.5.2.3 ***Guideline 3 (Fault Tolerance)***

Guideline 3 centres on ensuring that the perception layer can operate in the presence of errors or recover from any perception errors that may occur. Participants evaluated Guideline 3 using the criteria presented above, and the results are shown in Figure 6.5.

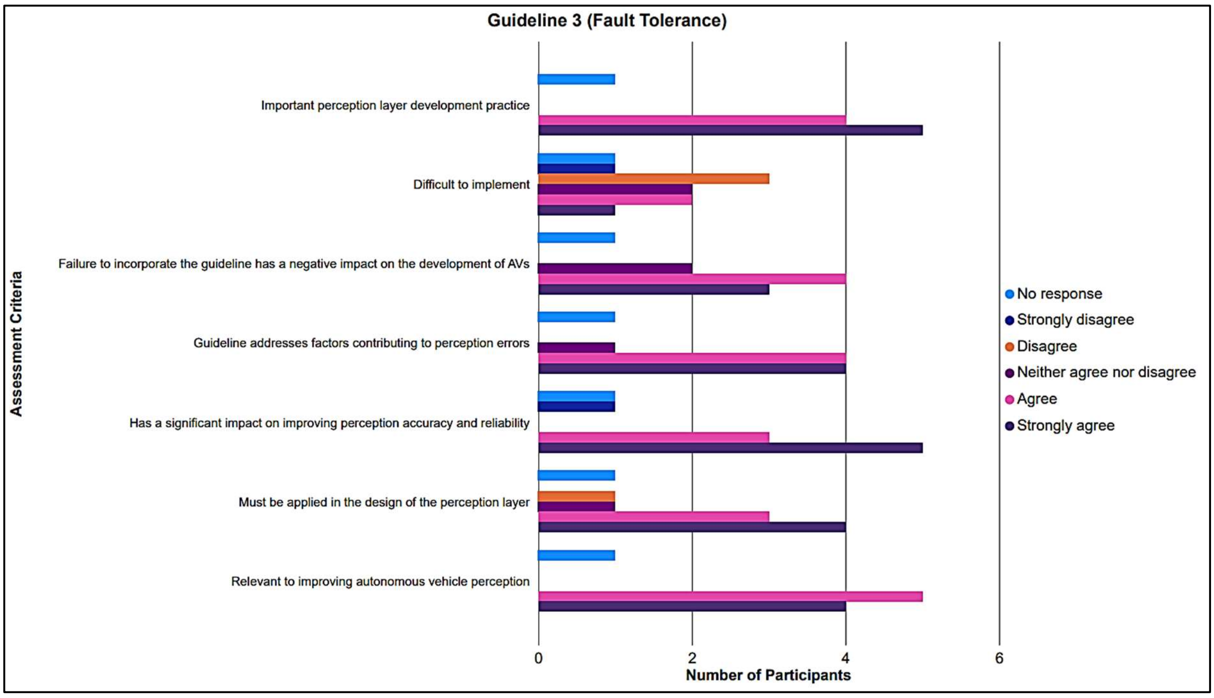

Figure 6.5: Guideline 3 Evaluation Results

Guideline Relevance in Improving Autonomous Vehicle Perception:

The data presented in Figure 6.5 indicate consensus among participants regarding the relevance of Guideline 3 (Fault Tolerance) in AV perception, with 40% strongly agreeing and 50% agreeing. Moreover, no participant rated the guideline as ‘neither agree nor disagree’, ‘disagree’, or ‘strongly disagree’.

Importance of the Guideline for Autonomous Vehicle Perception Layer Development:

The results illustrated in Figure 6.5 demonstrate that 50% of participants strongly agreed that Guideline 3 (Fault Tolerance) is an important AV perception development practice, with an additional 40% agreeing. Notably, no participant disputed the importance of the guideline.

Guideline Address Factors Contributing to Perception Errors:

Figure 6.5 illustrates that 40% of participants strongly agreed that Guideline 3 (Fault Tolerance) effectively addresses various factors contributing to perception errors, with an additional 40% agreeing. Moreover, 10% of the participants indicated that they 'neither agree nor disagree'.

Significant Impact of the Guideline on Improving Perception Accuracy and Reliability:

Participants evaluated the significance of Guideline 3 (Fault Tolerance) in improving perception accuracy and reliability. The results presented in Figure 6.5 show that 50% of the participants strongly agreed to its significance, whereas an additional 30% agreed. conversely, 10% of the participants expressed disagreement.

Necessity of Applying the Guideline in Perception Layer Design:

According to the results in Figure 6.5, 40% of participants strongly agreed and 30% agreed that Guideline 3 (Fault Tolerance) must be applied in the design and development of the AV perception layer, aiming to minimise perception errors and improve accuracy. However, 10% of the participants disagreed with the guideline, and an additional 10% neither agreed nor disagreed.

Implementation Difficulty of the Guideline in Autonomous Vehicle Perception Layer Development:

The data presented in Figure 6.5 indicates that only 10% of participants strongly agreed that it is difficult to implement guideline 3 (Fault Tolerance) in the development of the AV perception layer, with an additional 20% agreeing. Furthermore, 20% neither agreed nor disagreed. However, a substantial proportion of participants disputed the difficulty of implementing guideline 3 (Fault Tolerance); specifically, 30% disagreed, and an additional 10% strongly disagreed.

Negative Impact of Failing to Incorporate the Guideline on Autonomous Vehicle Perception Accuracy and Reliability:

Figure 6.5 demonstrates that most participants (30% strongly agreed, 40% agreed) believe that it is crucial to incorporate guideline 3 (Fault Tolerance) in the AV perception layer development. An additional 20% of participants remained neutral, neither agreeing nor disagreeing. Remarkably, no participants disagreed with the guideline.

6.5.2.4 ***Guideline 4 (Real-time Data Processing)***

Guideline 4 is about integrating edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing, as the integration offers more advantages. Participants evaluated Guideline 4 using the criteria presented above, and the results are shown in Figure 6.6.

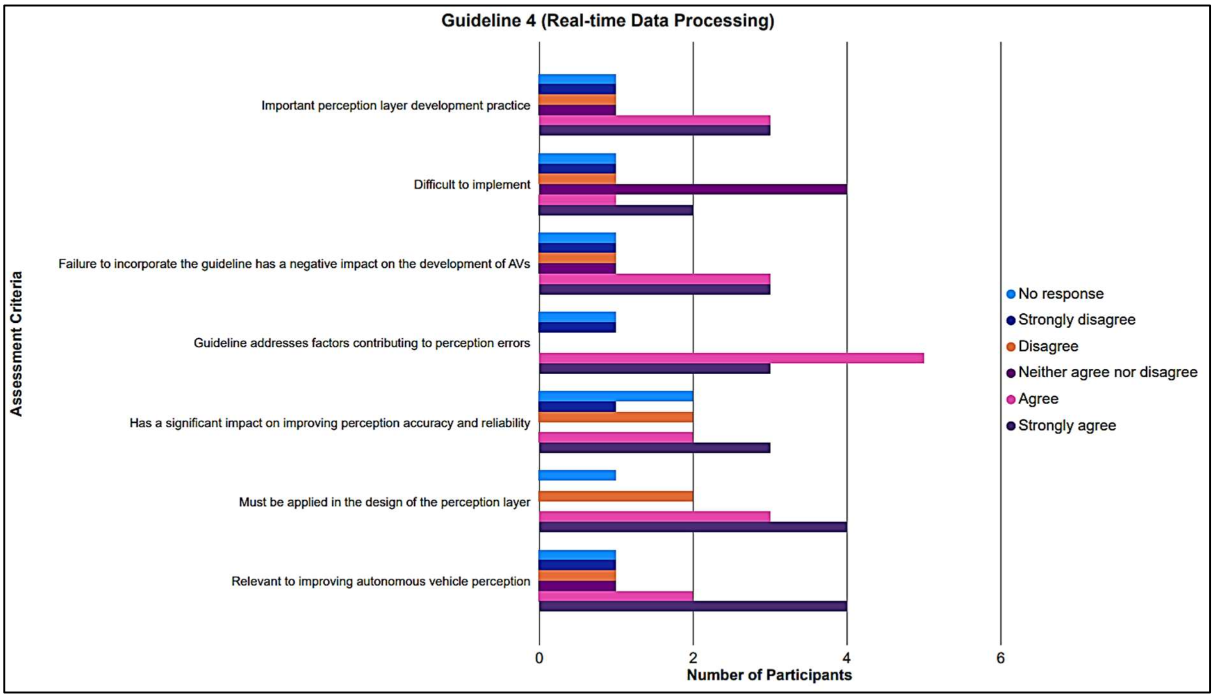

Figure 6.6: Guideline 4 Evaluation Results

Guideline Relevance in Improving Autonomous Vehicle Perception:

The data presented in Figure 6.6 indicates that a significant majority of participants (60%) acknowledged the relevance of Guideline 4 (Real-time Data Processing) in improving AV perception, with 40% strongly agreeing and 20% agreeing. Only a small proportion (10%) neither agreed nor disagreed. However, a notable minority (20%) disagreed with the guideline's relevance, with 10% strongly disagreeing and 10% disagreeing.

Importance of the Guideline for Autonomous Vehicle Perception Layer Development:

Participants evaluated the importance of Guideline 4 (Real-time Data Processing) in the development of the AV perception layer. The data presented in Figure 6.6 shows that 30% of the participants strongly agreed, 30% agreed, and a further 10% neither agreed nor disagreed with its importance. Conversely, 10% of the participants disagreed, with an additional 10% strongly disagreeing.

Guideline Address Factors Contributing to Perception Errors:

The data presented in Figure 6.6 indicates that a significant majority of participants (80%) agreed that Guideline 4 (Real-time Data Processing) addresses various factors that contribute to AV perception errors, with 30% strongly agreeing and 50% agreeing. However, a notable 10% strongly disagreed.

Significant Impact of the Guideline on Improving Perception Accuracy and Reliability:

Figure 6.6 indicates that 30% of participants strongly agreed that Guideline 4 (Real-time Data Processing) significantly improves AV perception, with 20% agreeing. In contrast, 20% disagreed, while an additional 10% strongly disagreed.

Necessity of Applying the Guideline in Perception Layer Design:

The data presented in Figure 6.6 indicates that 40% of participants strongly agreed that Guideline 4 (Real-time Data Processing) must be applied in the design and development of the AV perception layer, with 30% agreeing. Nevertheless, a minority (20%) disagreed with this necessity.

Implementation Difficulty of the Guideline in Autonomous Vehicle Perception Layer Development:

The data presented in Figure 6.6 indicates that 20% of the participants strongly agreed that it is difficult to implement Guideline 4 (Real-time Data Processing), with 10% agreeing. The results further indicate that 40% neither agreed nor disagreed. Additionally, 20% of the participants indicated that the implementation of Guideline 4 (Real-time Data Processing) is not difficult, with 10% disagreeing and 10% strongly disagreeing.

Negative Impact of Failing to Incorporate the Guideline on Autonomous Vehicle Perception Accuracy and Reliability:

The data presented in Figure 6.6 shows that 30% of the participants strongly agreed, with an additional 30% agreeing that failure to implement Guideline 4 (Real-time Data Processing) could have a negative impact on the AV perception accuracy and reliability, and a further 10% neither agreed nor disagreed. Conversely, 10% of the participants disagreed, with an additional 10% strongly disagreeing.

6.5.2.5 *Guideline 5 (Legal and Moral Considerations)*

Guideline 5 emphasises researching ethical, legal, and societal issues to improve safety and reliability, informing the development of relevant standards and legislation to address ethical and legal issues tailored to the South African region. Participants evaluated Guideline 5 using the criteria presented above, and the results are shown in Figure 6.7.

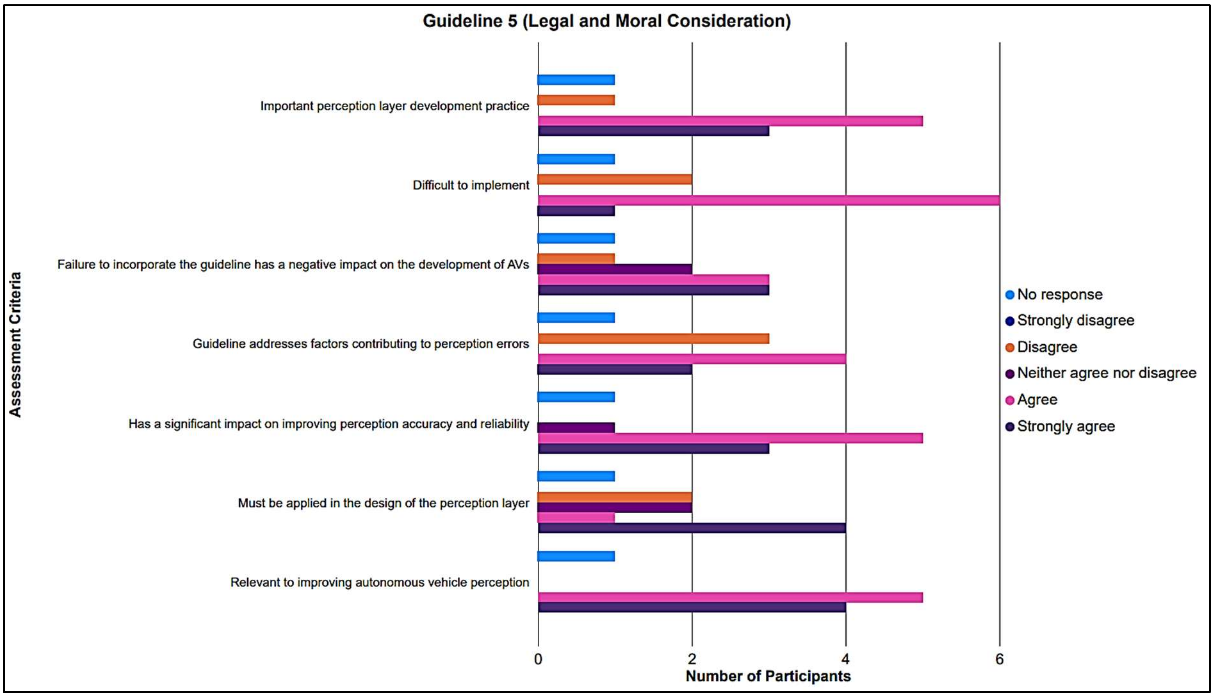

Figure 6.7: Guideline 5 Evaluation Results

Guideline Relevance in Improving Autonomous Vehicle Perception:

Figure 6.7 presents results on the relevance of guideline 5 (Legal and Moral Considerations) in improving AV perception. The results demonstrate a strong consensus among participants, with 40% strongly agreeing and an additional 50% agreeing with its relevance. As a result, the data generally shows that guideline 5 (Legal and Moral Considerations) is considered relevant to improving AV perception capabilities. Moreover, no participant disputed the relevance of guideline 5 (Legal and Moral Considerations).

Importance of the Guideline for Autonomous Vehicle Perception Layer Development:

The data presented in Figure 6.7 reveal that a significant majority of the participants (80%) generally agreed that guideline 5 (Legal and Moral Considerations) is an important aspect of AV perception layer practice, while 30% strongly disagreed and 50% disagreed. However, a minority (10%) disagreed.

Guideline Address Factors Contributing to Perception Errors:

The results in Figure 6.7 indicate that 20% of participants strongly agreed that guideline 5 (Legal and Moral Considerations) can effectively address factors that contribute to AV perception errors, with 40% agreeing. Nevertheless, 30% of the participants disagreed.

Significant Impact of the Guideline on Improving Perception Accuracy and Reliability:

Figure 6.7 presents results on the significance of guideline 5 (Legal and Moral Considerations) in improving AV perception. The data indicates that 30% strongly agreed and 50% agreed. An additional 10% expressed neutrality (neither agree nor disagree). The results further reveal that no participant rated the guideline as ‘disagree’ or ‘strongly disagree’.

Necessity of Applying the Guideline in Perception Layer Design:

The data presented in Figure 6.7 indicates that 40% of the participants strongly agreed with the necessity of applying guideline 5 (Legal and Moral Considerations) in the design of the AV perception layer, with 10% disagreeing. An additional 20% of participants remained neutral, neither agreed nor disagreed, and 20% indicated disagreement.

Implementation Difficulty of the Guideline in Autonomous Vehicle Perception Layer Development:

Figure 6.7 presents the evaluation results on whether the implementation of guideline 5 (Legal and Moral Considerations) in AV perception layer development is difficult. 10% strongly agreed, indicating that it is difficult to implement guideline 5, with an additional 60% agreeing. Nevertheless, 20% of the participants disagreed.

Negative Impact of Failing to Incorporate the Guideline on Autonomous Vehicle Perception Accuracy and Reliability:

The results presented in Figure 6.7 suggest a considerable concern among participants regarding the potential negative consequences of neglecting guideline 5 (Legal and Moral Considerations) on AV perception accuracy and reliability. The results revealed that 30% of the participants strongly agreed that the absence of guideline 5 (Legal and Moral Considerations) could negatively impact AV perception, while 30% agreed. An additional 20% of participants remained neutral, neither agreed nor disagreed, and 10% expressed disagreement.

6.5.2.6 ***Guideline 6 (Testing and Validation)***

Guideline 6 is about testing perception algorithms in real-world conditions or highly realistic simulations to enable the vehicle to learn more about different environments and scenarios. Participants evaluated Guideline 6 using the criteria presented above, and the results are shown in Figure 6.8.

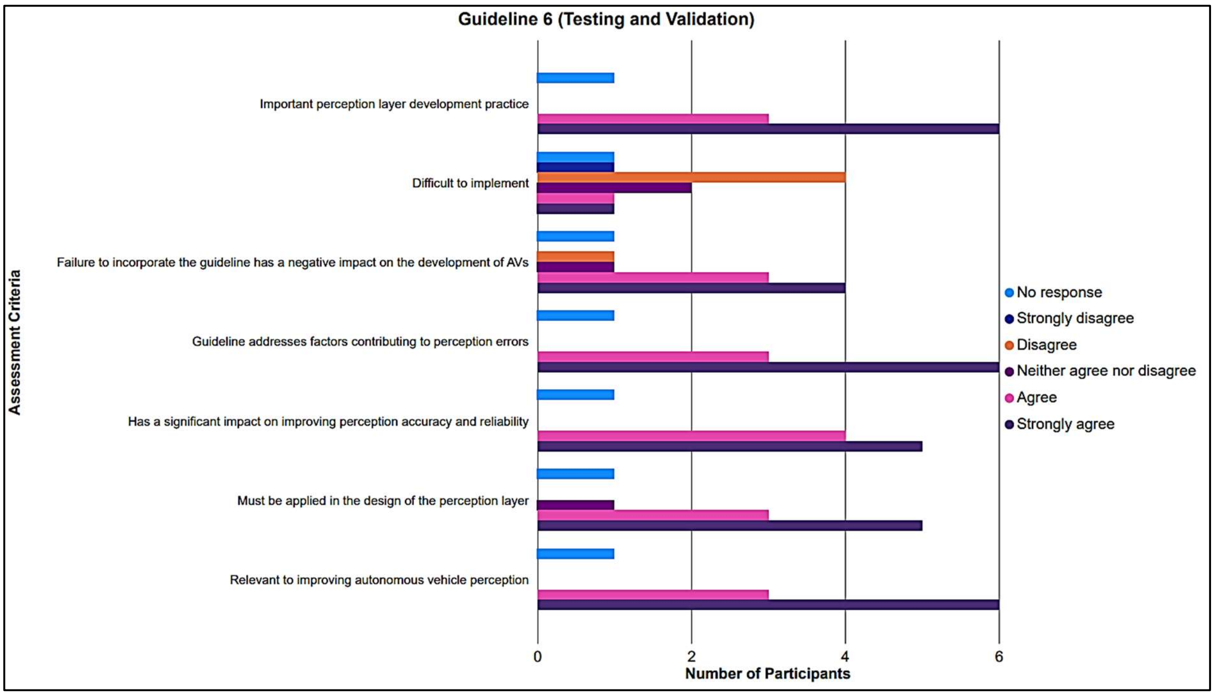

Figure 6.8: Guideline 6 Evaluation Results

Guideline Relevance in Improving Autonomous Vehicle Perception:

The data presented in Figure 6.8 indicate a strong consensus among participants regarding the relevance of Guideline 6 (Testing and Validation) for AV perception, with 60% strongly agreeing and 30% agreeing. Additionally, no participant rated the guideline as ‘neither agree nor disagree’, ‘disagree’, or ‘strongly disagree’.

Importance of the Guideline for Autonomous Vehicle Perception Layer Development:

The participants' evaluation of the importance of Guideline 6 (Testing and Validation) in the development of the AV perception layer indicates that 60% of the participants strongly agreed, while 30% agreed with its importance, as shown in Figure 6.8. The results further reveal that no participant disagreed or strongly disagreed with its importance.

Guideline Address Factors Contributing to Perception Errors:

Participants evaluated the effectiveness of Guideline 6 (Testing and Validation) in addressing factors contributing to perception errors. The results presented in Figure 6.8 indicate that most participants expressed positive agreement, with 60% strongly agreeing and 30% agreeing.

Significant Impact of the Guideline on Improving Perception Accuracy and Reliability:

The findings illustrated in Figure 6.8 demonstrate a strong consensus among participants regarding the significant impact of Guideline 6 (Testing and Validation) on the development of AV perception and its role in improving accuracy and reliability. A majority of participants expressed positive agreement, with 50% strongly agreeing and 40% agreeing. Furthermore, none of the participants adopted a neutral stance (neither agreed nor disagreed) or disagreed with guideline 6.

Necessity of Applying the Guideline in Perception Layer Design:

The results presented in Figure 6.8 reveal that a substantial majority (50% strongly agreed, 30% agreed) of participants concurred that Guideline 6 (Testing and Validation) must be applied in the AV perception layer. The results further indicate that 10% of the participants neither agreed nor disagreed.

Implementation Difficulty of the Guideline in Autonomous Vehicle Perception Layer Development:

The data depicted in Figure 6.8 indicates that a small proportion (20%) agreed that it is difficult to implement Guideline 6 (Testing and Validation) in AV perception layer development, with

10% strongly disagreeing and 10% agreeing. Furthermore, 20% neither agreed nor disagreed. However, a majority (50%) disputed the implementation difficulty of Guideline 6 (Testing and Validation); specifically, 40% disagreed, and an additional 10% disagreed.

Negative Impact of Failing to Incorporate the Guideline on Autonomous Vehicle Perception Accuracy and Reliability:

The data presented in Figure 6.8 shows that 40% of the participants strongly agreed, with an additional 30% agreeing that failure to incorporate Guideline 6 (Testing and Validation) in AV perception layer development can have a negative impact on the AV perception accuracy and reliability, and a further 10% neither agreed nor disagreed. Conversely, 10% of the participants disagreed, indicating that failure to incorporate Guideline 6 (Testing and Validation) in AV perception layer development would not necessarily have a negative impact.

6.5.2.7 *Guideline 7 (Artificial Intelligence)*

Guideline 7 emphasises the necessity of training artificial intelligence (AI) algorithms to accurately recognise South Africa's unique road signs, environmental conditions, and driving behaviours. Participants evaluated Guideline 7 using the criteria presented above, and the results are shown in Figure 6.9.

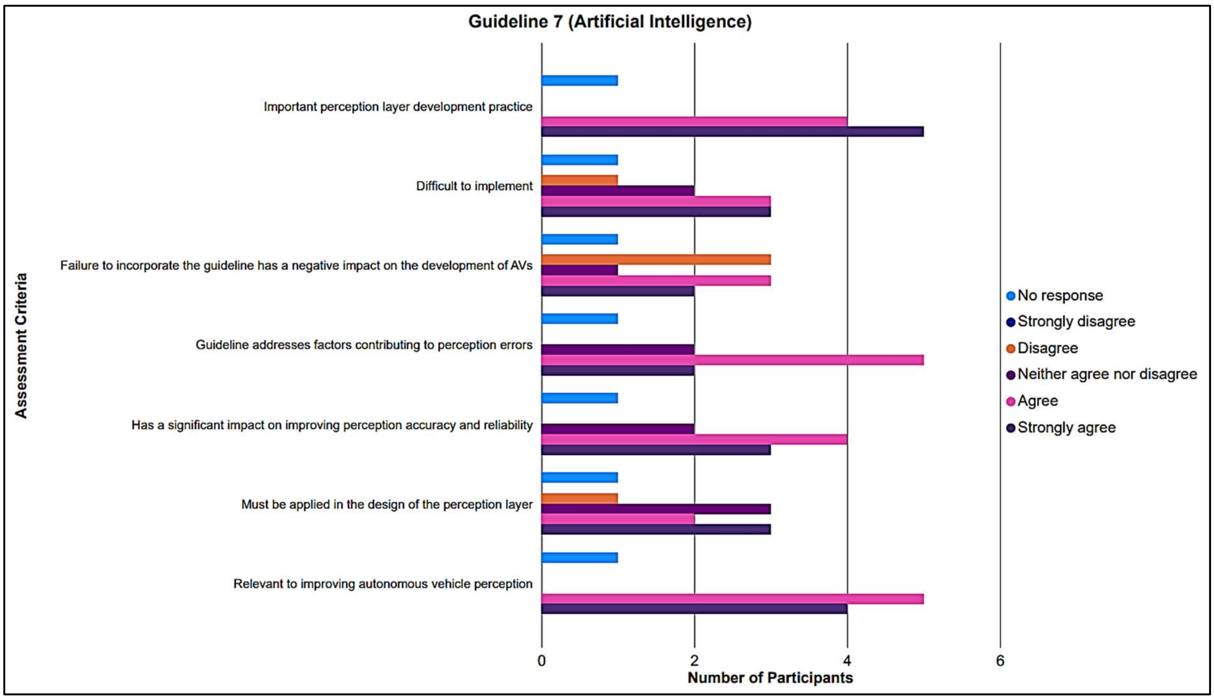

Figure 6.9: Guideline 7 Evaluation Results

Guideline Relevance in Improving Autonomous Vehicle Perception:

Participants evaluated the relevance of guideline 7 (Artificial Intelligence) in improving AV perception. The results illustrated in Figure 6.9 indicate that 40% of the participants strongly agreed to its relevance, and an additional 50% agreed. The results further reveal that no participants disagreed with the relevance of guideline 7 (Artificial Intelligence).

Importance of the Guideline for Autonomous Vehicle Perception Layer Development:

The data presented in Figure 6.9 depicts that 50% strongly agreed that guideline 7 (Artificial Intelligence) is important in AV perception layer development, with 40% agreeing. Furthermore, none of the participants disagreed with guideline 7.

Guideline Address Factors Contributing to Perception Errors:

The findings in Figure 6.9 demonstrate a strong consensus among participants that guideline 7 (Artificial Intelligence) addresses factors contributing to perception errors. Most participants expressed a positive agreement, with 20% strongly agreeing and 50% agreeing. Additionally, 20% of the participants neither agreed nor disagreed.

Significant Impact of the Guideline on Improving Perception Accuracy and Reliability:

Figure 6.9 illustrates that most participants (30% strongly agreed, 40% agreed) believe that guideline 7 (Artificial Intelligence) significantly impacts AV perception accuracy and reliability. An additional 20% of participants remained neutral, neither agreeing nor disagreeing.

Necessity of Applying the Guideline in Perception Layer Design:

According to the results in Figure 6.9, 30% of participants strongly agreed and 20% agreed that guideline 7 (Artificial Intelligence) must be applied in the design and development of the AV perception layer, aiming to minimise perception errors and improve accuracy. However, 10% of the participants disagreed, suggesting that guideline 7 (Artificial Intelligence) may not be applied in the design of the AV perception layer, with a notable 30% neither agreeing nor disagreeing.

Implementation Difficulty of the Guideline in Autonomous Vehicle Perception Layer Development:

Figure 6.9 illustrates that 30% of participants strongly agreed that guideline 7 (Artificial Intelligence) is difficult to implement in the development of the AV perception layer, with an additional 30% agreeing. Furthermore, 20% neither agreed nor disagreed, expressing neutrality. However, only 10% of participants disagreed, suggesting that the guideline is not difficult to implement.

Negative Impact of Failing to Incorporate the Guideline on Autonomous Vehicle Perception Accuracy and Reliability:

The data presented in Figure 6.9 shows that 20% of the participants strongly agreed, with an additional 30% agreeing that failure to implement guideline 7 (Artificial Intelligence) can have a negative impact on the AV perception accuracy and reliability, and a further 10% neither agreed nor disagreed. Conversely, 30% of the participants disagreed.

6.6 Summary

This chapter presented the evaluation results as presented by the expert participants. Adhering to an ex-post naturalistic evaluation, the study adopted the Human Risk and Effectiveness as the evaluation strategy to evaluate and validate the preliminary guidelines, thereby informing the formulation of final guidelines. To evaluate the effectiveness of the initial guidelines, a questionnaire consisting of both open-ended and closed-ended questions was administered to participants. Furthermore, this chapter discussed the demographics of the participants who contributed to the data collection phase. This chapter also presented the results related to perception tasks and guidelines from the evaluation process. The presentation of the guidelines' findings followed a specific criterion used during the formulation of the questionnaire. To analyse the collected data, the study employed a descriptive data analysis approach, facilitated by Microsoft Excel and Power BI to visually represent the collected quantitative data. These findings are interpreted and discussed in Chapter 7.

Chapter 7: Discussion

7.1 Introduction

This chapter provides a discussion of the results presented in Chapter 6 and presents the final set of guidelines informed by literature and subsequent experts' evaluations. This chapter aims to answer the main research question of this study

How can perception errors be reduced in Autonomous Vehicle System Architecture to improve safety and limit technical challenges?

7.2 Expert Evaluation Results Discussion

This subsection presents a discussion of the results from Chapter 6 regarding perception tasks and guidelines in response to the research sub-questions.

7.2.1 Autonomous Vehicles Perception Tasks

This section discusses the research sub-question 1 formulated as follows:

RSQ1: What should be the key tasks of the perception layer of the Autonomous Vehicles System Architecture?

The main aim of this question was to identify what the perception layer is supposed to do and to align the perception tasks with the guidelines developed in this study. It was important to understand the perception layer tasks so as to align the guidelines with these tasks. Participants were asked to indicate the importance of the AV perception tasks identified from the literature, as presented in section 3.5 and Figure 7.1 below.

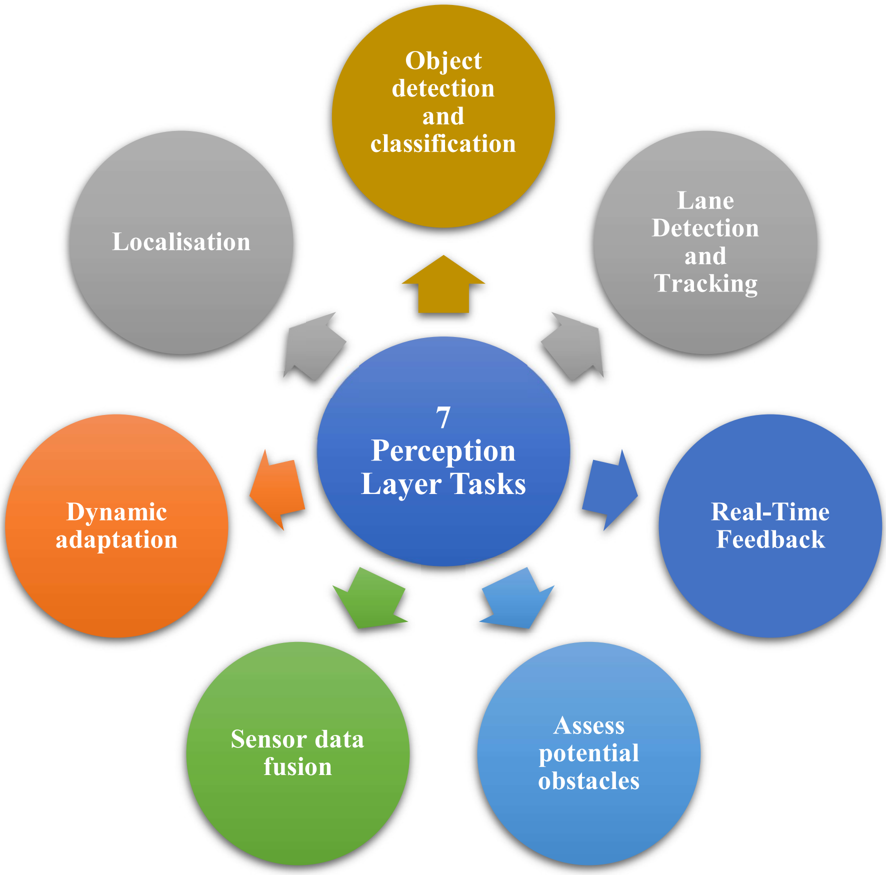

Figure 7.1: Perception layer tasks (Author's own work)

The results in section 6.5.1 confirm and validate the perception tasks identified from the literature:

- **Object Detection and Classification**

  The results from the evaluation process revealed that object detection is undoubtedly the most critical task of the AV perception layer. Participant 1 mentioned that correct classification is a crucial AV perception task. Furthermore, Participant 10 commented, *"Environmental context recognition; identifying environmental conditions like temperature or light intensity, to adapt system behavior accordingly",* proposing it as an additional task. However, this task fits the description of '*Object Detection and Classification*' as discussed in section 3.5.1. As such, this study incorporates this task under object detection and classification. Object detection and classification facilitate the recognition and classification of the detected environmental objects based on their inherent characteristics and behavioural patterns. Participant 8 added that, "*object detection and classification are crucial tasks in computer tasks enabling machines to identify and categorise objects*". AV developers and engineers need to focus on developing and testing highly accurate and robust object detection and classification algorithms, especially for challenging scenarios.

- **Real-Time Feedback**

Participant 1 further supported the results in section 6.5.1 on the real-time feedback processing, clarifying its significance to the overall development of AVs. Participant 1 noted, "*real-time feedback would be a good feature in these vehicles especially for traffic regulation, but in my opinion not regarded as a necessity - vehicle to vehicle communication is more important than real-time feedback. Vehicles need to communicate to a level that include environmental danger areas - flooding, fire, explosion*". This perspective underscores the necessity of considering the broader Vehicle-to-Everything (V2X) communication, extending beyond the initial scope of communication between the perception layer and decision layer. Supporting this, Khan et al. (2022) stated that access to external data improves decision-making in AVs. Consequently, the '*Real-time feedback'* task has been reformulated as '*Vehicular Communication and Real-Time Data Processing*' to encompass this expanded scope as shown in Figure 7.2. Fast and accurate feedback from sensors and algorithms is necessary for timely communication, decision-making, and control actions to ensure safety and responsiveness.

Figure 7.2: Revised perception tasks

On the tasks: Lane Detection and Tracking, Sensor Data Fusion, Assessing Potential Obstacles, Dynamic Adaptation, and Localisation:

Participants did not suggest or infer any changes on lane detection and tracking, sensor data fusion, assessing potential obstacles, dynamic adaptation, and localisation. Rather, they emphasised their importance. The results in section 6.5.1 validated these perception layer tasks.

Participants 4 and 9 noted that assessing potential obstacles is important to assist with obstacle avoidance. The perception layer not only identifies obstacles but also evaluates and understands their nature and depth, ensuring the safety of AVs by monitoring the environment for hazards and reacting accordingly (Ondruš et al., 2020). Participant 1 added that in simple terms, "*AVs must understand the depth of obstacles but not as important as the size, movement and nature of the obstacle*". This suggests that developers should prioritise algorithms and sensor systems that can accurately detect and classify potential obstacles, such as pedestrians, cyclists, and other vehicles.

The results presented in section 6.5.1 suggest that lane detection and subsequently tracking them is a critical AV perception task. Participant 7 emphasised its importance by noting that a vehicle *"can't drive on its own without detecting lanes".* Accurate lane detection and tracking are essential for maintaining lane position, avoiding collisions, and navigating complex traffic scenarios. Participant 1 further commented on the dynamic adaptation task and mentioned that *"Changes to local/environment in terms of maps, road conditions will play a role in updates of the algorithms".* This shows the need for AVs to adapt to changing traffic conditions, unexpected events, and environmental factors. This requires robust algorithms for real-time perception and decision-making.

The results also showed that integrating data from multiple sensors (e.g., cameras, LiDAR, RADAR) can improve overall perception accuracy and robustness, especially in challenging environments. Furthermore, they revealed that precise localisation is crucial for safe navigation, path planning, and overall vehicle control.

7.2.2 Emergent Tasks

Four tasks emerged from the data collection process and were subsequently approved by the researcher. Participants suggested these additional tasks: Motion Forecasting, Safety System Integration, Free Space Detection, and Weather Condition Detection and Response, which are also crucial for accurate AV perception.

- **Motion Forecasting**
  Participant 8 recommended motion forecasting as an additional task and added that it assists in "*predicting the future motion of the detected objects*". This task is important as it allows the perception layer to predict forthcoming motions of other objects in the environment. AVs need to be able to detect and predict the trajectories of other objects in the environment (Su, 2023). There are two main approaches to motion forecasting: Scenario-based Motion Forecasting and Perception-based Motion Forecasting (Shi et al., 2025). Scenario-based motion forecasting predicts future motions by analysing past states and relevant environmental context. These can be scenarios used to train the models or historical events collected on the road (Shi et al., 2025). Perception-based motion forecasting uses raw perception data from the sensors to predict future motions, allowing the model to learn relevant representations directly from raw data (Shi et al., 2025).
- **Safety Systems Integration**

Participants 1 and 2 advocated for the importance of integrating safety systems. Participant 1 further commented that the safety systems can include *"emergency response to errors, accidents, environmental changes, vehicle-to-vehicle communication, and vehicle-to-authorities communication"*. This integration enables a comprehensive report of all safety systems within the AV, allowing the perception layer to relay essential information to the decision layer and to support other perception layer tasks, such as assessing the obstacles.

- **Free Space Detection**

  Free space detection is an addition to object detection, aiming to enable AVs to detect and identify drivable areas and avoid detected obstacles. This is supported by participant 8, who mentioned that the task is aimed at *"identifying areas in the environment that are free from obstacles"*. This task is also useful in identifying available and occupied parking spaces in parking lots (Nahata and Othman, 2023).

- **Weather Condition Detection and Response**

  Participant 8 further suggested Weather Condition Detection and Response. Complementary to tasks such as sensor fusion, which aims to provide the vehicle with an accurate image of the environment even under adverse weather conditions, AVs must be able to detect the prevailing weather conditions for an appropriate response. The results proposed this task as precise detection of weather conditions allows the AV to adapt its perception and control strategies to maintain safe and effective operations.

Figure 7.3 below presents perception layer tasks identified from the literature and the four tasks that emerged from the evaluation process. The emergent tasks are represented in red:

Figure 7.3: Final Perception Layer Tasks with Emergent tasks

7.2.3 Guidelines

This section discusses research sub-questions 2 and 3, which are formulated as follows:

RSQ2: What are the technical enablers and challenges encountered in autonomous vehicles?

RSQ3: What guidelines could be followed to reduce perception errors in the Autonomous Vehicle System Architecture?

The question on the application of the guideline in design seeks to determine the 'level of authority' of the guideline. The level of authority refers to an indication of whether or not the guideline is crucial to be followed or less crucial (Dix et al., 2004; Cowley, 2009). The level of authority is analysed and interpreted as follows:

5 – Strong Research Support

- Cumulative and compelling, supporting research-based evidence.
- At least one formal, rigorous study with contextual validity
- No known conflicting research-based findings

- Expert opinion agrees with the research.

4 – Moderate Research Support

- Cumulative research-based evidence
- There may or may not be conflicting research-based findings.
- Expert opinion
  - Tends to agree with the research, and
  - A consensus seems to be building.

3 – Weak Research Support

- Limited research-based support
- Conflicting research-based findings may exist, and/or
- There is a mixed agreement of expert opinions.

2 – Strong Expert Opinion Support

- No research-based evidence
- Experts tend to agree, although there may not be a consensus.
- Multiple supporting expert opinions in textbooks, style guides, etc.
- Generally accepted as a 'best practice' or reflects 'state of practice.'

1 – Weak Expert Opinion Support

- No research-based evidence
- Limited or conflicting expert opinion

7.2.3.1 ***Guideline 1 (Sensor Fusion)***

Sensor data fusion is one of the crucial tasks of AV perception. Oudeif, Mohsen and Alasry (2024) define sensor fusion as a robust and precise algorithm capable of achieving optimal performance under diverse weather conditions, supplanting human vision sense in AV operations. The technical challenges (detailed in section 4.3) of individual sensor limitations and failures, and adverse weather conditions can be mitigated by deploying robust sensor fusion algorithms to compensate for individual sensor limitations and allowing the ability for clear perception in adverse weather conditions, thereby improving object detection and classification, lane detection and tracking, the assessment of obstacles, free space detection and sensor data fusion. From this emerges guideline 1 (sensor fusion), which aims to establish more advanced and robust sensor fusion algorithms to overcome individual sensor limitations and provide a clear picture of the environment from different angles under various weather conditions.

Consequently, guideline 1, as formulated in section 5.3, pertains to establishing robust sensor fusion algorithms to integrate data generated by individual sensors into a comprehensive view.

The implementation of guideline 1 is crucial in the foundational design and subsequent development of the AV perception layer. Participant 8 noted, *"The guideline must be applied in the foundation of the design (Design of AV perception layer)"*. The comment affirms its importance and relevance as a fundamental building block for AV perception layer development. Moreover, the results presented in section 6.5.2 and visually represented in Figure 6.3 suggest that Guideline 1 (sensor fusion) is considered essential, relevant, and significant in improving AV perception accuracy.

Sensor fusion cannot be overlooked as it is critical for ensuring the reliability, accuracy, and precision of the AV perception layer. It must be applied and incorporated into the development of the AV perception layer to mitigate perception errors for a safer driving experience. Sensor fusion offers a potential solution to address various factors that contribute to perception errors. Notably, participant 9 asserted that "*It (guideline 1) deals directly with helping to address the challenge of object and lane detection in various weather conditions"*. This comment aligns with existing literature. Oudeif, Mohsen and Alasry (2024) stated that sensor fusion algorithms can achieve optimal performance under unfavourable weather conditions as they supplant human vision. Consequently, sensor fusion offers a remedy for lane detection challenges, adverse weather conditions, and overall AV detection capabilities. Participant 9 further elaborated that guideline 1 is precisely aimed at improving AV perception accuracy and reliability.

The results indicated a lack of clear consensus regarding the level of implementation difficulty. These insights warrant further investigation into the reasons behind neutral responses and differing opinions for clear and valuable insights. However, Participant 9 commented, "*It will certainly not be easy and need lots of trial and error, but will prove worth it to keep people safe"*. This suggests that while the implementation of sensor fusion may present challenges, its potential benefits for safety justify the need for more research and testing, ensuring minimal errors. More advanced sensor fusion algorithms will provide a clear environmental context for safe driving.

In conclusion, Guideline 1 (sensor fusion) was empirically validated as a crucial requirement for improving the AV perception layer, with participants largely acknowledging the value and necessity of sensor fusion for robust AV perception. The level of authority for

Guideline 1 (sensor fusion) is **Moderate Research Support (4).** There is cumulative research-based support as explored in the literature (section 4.6.2.2), revealing that it is a critical requirement, but still needs to be explored to develop advanced sensor fusion algorithms. This level of authority is further derived from the overall participants' opinions, which indicate a robust consensus advocating for the guideline to be applied in the design and development of AVs. Additionally, results showed the importance of incorporating sensor fusion principles in the development of AVs. While some variability exists in its implementation difficulty and the absolute necessity of its application, a consensus seems to be building among participants, necessitating more research on its implementation. Participant 9 emphasised the critical nature of this guideline and noted, "*If overlooked in design (Guideline 1), the failure of the entire product is at risk with possible severe safety concerns*". This comment aligns with the results on the relevance and importance of the guideline, as presented in Figure 6.3. The overall results suggest that guideline 1 was not only suggested in this study, but it is a critical requirement to ensure AV safety. Agreeing with this conclusion, Wang (2021) asserted that sensor fusion is at the centre of AV perception. Table 7.1 presents the final formulation of guideline 1 (sensor fusion), indicating the level of authority.

Table 7.1: Refined presentation of Guideline 1

GUIDELINE 1 (SENSOR FUSION): ESTABLISH ALGORITHMS FOR SENSOR FUSION IN AV PERCEPTION					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Develop and implement more advanced, robust, and precise sensor fusion algorithms that combine the large amount of data generated by individual sensors and related information in a unified format. The algorithms must synchronise all sensor data acquisitions based on a common timestamp to guarantee accurate interpretations.					
Rationale: The sensor fusion algorithms leverage the strengths of different sensors to overcome the limitations of individual sensors and enhance perception accuracy. The algorithms improve accuracy, reliability, and fault tolerance and decrease uncertainty in redundant data measurements. The integration of sensors could help address the challenge of object and lane detection in adverse weather conditions by providing a clear picture of the environment from different angles.					
References: Realpe, Vintimilla and Vlacic, 2016; Van Brummelen et al., 2018; Rosique et al., 2019; PAS 1880:2020; Wang, 2021; Dauptain et al., 2022; Hasanujjaman, Chowdhury and Jang, 2023; Nahata and Othman, 2023; Oudeif, Mohsen and Alasry, 2024					

7.2.3.2 ***Guideline 2 (Sensor Calibration and Maintenance)***

The challenge of environmental factors such as adverse weather conditions and sensor limitations, such as sensor drift, degradation, and calibration errors, can be managed by implementing self-cleaning mechanisms and regularly updating and calibrating sensors for precise object and weather detection and classification, lane and free space detection, obstacle assessment, and fostering dynamic adaptation and accurate localisation. From this, guideline 2 (Calibration and maintenance) is derived, focusing on continuously improving and updating sensors to minimise errors caused by sensor drift and degradation, and developing sensor cleaning strategies to handle adverse weather conditions. Guideline 2 (Sensor calibration and maintenance), as formulated in section 5.3, refers to the constant improvement and update of sensors to help reduce errors caused by sensor drift and degradation.

The results in Figure 6.4 validated the importance and relevance of guideline 2 in AV perception layer development. The importance and significance of this guideline lie in the proactive sensor calibration and maintenance to ensure a resilient system. Participant 8 commented that "*regular maintenance is crucial in accuracy and reliability*". This comment further supports the literature by Kumar et al. (2022), who mentioned that maintenance is important throughout the lifecycle of AVs.

The implementation of guideline 2 (Sensor calibration and maintenance), as suggested by the results in Figure 6.4, is relatively feasible. A significant proportion of participants (40%) generally disagreed with its implementation difficulty. However, there is a further 40% that remained neutral, indicating a lack of consensus among participants and warrants further research into the factors influencing their standpoint. Participant 4 noted, "*It (guideline 2) should be tested for people's safety*". This suggests intensive testing to realise the guideline's potential, ensuring safety and guaranteeing optimal functionality. Furthermore, the results indicated that it is critical to apply guideline 2 in the design and development of the AV perception layer, and failure to do so may negatively impact AV perception. This underscores the need for intensive testing of guideline 2 design during implementation, as it is essential for ensuring accurate, safe, and reliable perception.

Guideline 2 plays a critical role in the design of the AV perception layer and should not be overlooked. The main role of guideline 2 is to ensure that there are minimal perception errors due to sensor drift and degradation. Participants 8 supported this and noted that "*It addresses factors that may help in maintaining a positive environment*". Participant 9 concurred, indicating that guideline 2 helps directly with addressing and rectifying perception errors in AVs to maintain a positive environment.

Guideline 2 was empirically validated and regarded as a critical requirement for ensuring AV perception safety. The level of authority for guideline 2 is **Moderate Research Support (4)**. This conclusion was made based on the following reasons: there is sufficient research that supports guideline 2 as an essential AV perception layer development practice. This includes standards such as ISO/PAS 21448:2019. The overall findings emphasise the importance of proactively considering sensor calibration and maintenance to ensure a resilient system. Participants 4 and 9 further stated that not incorporating and enforcing guideline 2 in the design and development of AVs would deliver a sub-par and unsafe vehicle. Table 7.2 presents the final formulation of guideline 2 (sensor calibration and maintenance), indicating the level of authority. Participants emphasised rigorous testing to ensure human safety, and this was included in the rationale of this guideline to emphasise this point. The improved rationale incorporates views from the participants that are highlighted in bold italic.

Table 7.2: Refined presentation of Guideline 2

GUIDELINE 2 (SENSOR CALIBRATION AND MAINTENANCE): REGULARLY CALIBRATE AND MAINTAIN THE VEHICLE SENSORS					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Constantly improve and update sensors to help reduce errors caused by sensor drift and degradation. Develop sensor cleaning strategies to cope with adverse weather conditions.					
Rationale: Sensor calibration and maintenance requirements are crucial for sensor fusion and implementing algorithms for obstacle detection, localisation, and mapping. Regular maintenance and updates may help to address any potential issues and keep the perception system up to date. ***Rigorously tested sensor calibration and maintenance mechanisms can help minimise perception errors, ensuring human safety.***					
References: ISO/PAS 21448:2019; Yeong et al., 2021; Dauptain et al., 2022; Kumar et al., 2022; Su, 2023					

7.2.3.3 ***Guideline 3 (Fault Tolerance)***

Fault tolerance plays a critical role in human safety. It enables safe operation until necessary repairs can be conducted. Errors from adverse weather, lighting, road conditions, sensor uncertainty and noise, sensor limitations, and failures are challenges that impede the safe operation of AVs. These challenges can be mitigated by employing a fault-tolerant system that allows AVs to recover from errors, thereby enabling the perception layer to perform its tasks as shown in Figure 7.3. From this, guideline 3 (Fault Tolerance) is derived, which encourages the use of additional sensors for increased coverage to enable AVs to operate effectively in the presence of errors. Guideline 3 (Fault tolerance), as formulated in section 5.3, refers to the ability of the perception layer to recover from errors to ensure safety and secure operations.

Guideline 3 is an important and relevant AV perception layer development practice. It undoubtedly addresses various factors, such as adverse weather conditions that can impede sensor abilities and lead to perception errors. Guideline 3 plays a critical role, not only in ensuring safety but also in ensuring customer trust. Participant 9 noted, "*Some (people) may be more inclined to buy if they know they can still drive their cars even with certain sensor faults with proper measures in place*". This underscores the criticality of guideline 3 in AV perception to ensure safety and customer trust.

The results in Figure 6.5 suggest that guideline 3 (Fault tolerance) must be applied in AV design, and failure to do so may negatively impact the overall AV perception capabilities. However, some participants differed and indicated that failure to incorporate the guideline does not have much impact on AV safety, particularly the vehicle's perception accuracy and reliability (Participant 9). Despite this, the results show that guideline 3 is a crucial requirement in AV perception and incorporating fault tolerance features could serve as a valuable selling point for AV manufacturers. Participant 9 further added, "*I think it would be very helpful for individuals on the road to be able to keep driving until they can properly be able to take care of whatever repairs are necessary*". This underscores the need for a fault tolerance perception layer for safety and ensuring people are not stuck on the road for long hours. It further suggests a potential link between safety and customer confidence.

The results indicated a lack of clear consensus regarding the level of implementation difficulty. These insights indicate a need for further investigation, potentially exploring the specific technical challenges and resource implications associated with implementing robust fault tolerance mechanisms in the AV perception layer. Participant 9 also mentioned that "*It (the implementation of guideline 2) could take a good amount of research and development but (I) believe it would be worth it.*" Participant 4 added, "*They should test a lot before realizing its potential.*"

In conclusion, guideline 3 (Fault tolerance) was empirically validated as a crucial element for improving the AV perception layer. It plays a critical role in ensuring safety and customer trust by ensuring people can drive their vehicle in the presence of errors until necessary repairs are conducted. A strong majority (80%) of participants agreed that this guideline should be integrated into the design and development of AVs. Since there is only one opposing viewpoint, consensus can be formed, and further research may prove useful. Consequently, the level of authority for guideline 3 is **Moderate Research Support (4)**. This is not only derived from the participants' opinions, but there is cumulative research support, such as the PAS 1880:2020 standard advocating for a fault-tolerant perception layer. Table 7.3 presents the final formulation of guideline 3 (Fault tolerance), indicating the level of authority.

Table 7.3: Refined presentation of Guideline 3

GUIDELINE 3 (FAULT TOLERANCE): ENSURE THE PERCEPTION SYSTEM IS ABLE TO RECOVER FROM ERRORS					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Additional sensor coverage should be considered to ensure safe and secure AV operations. This can be achieved by installing additional sensors. The implementation of a fault-tolerant system must be able to detect the error, discover the error location, and recover from the detected error.					
Rationale: The degradation or loss of a single sensor can make it necessary to bring the vehicle to a stop or cause safety issues. It is necessary to have measures in place for AVs to learn to operate in the presence of faults to avoid unplanned behaviours, especially those resulting from sensor faults.					
References: Realpe, Vintimilla and Vlacic, 2016; Pas 1880:2020; Zhao et al., 2024					

7.2.3.4 *Guideline 4 (Real-time Data Processing)*

Real-time data processing is critical for effective navigation and communication with other vehicles and the surrounding environment (Boukerche and Sha, 2021; Biswas and Wang, 2023). The challenge of inadequate processing requirements (detailed in section 4.3.3) can be mitigated by employing the combination of Edge Computing and 5G for faster data processing, improving the vehicular communication and real-time data processing task. From this emerges guideline 4 (Real-Time Data Processing), aiming to ensure robust V2X communication by integrating edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing. Guideline 4 (Real-time Data Processing), as formulated in section 5.3, refers to integrating edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing, as the integration offers more advantages.

The results in Figure 6.6 suggest that 60% of the participants believe that guideline 4 is relevant and important in the development of the AV perception layer. However, 20% of participants generally disagreed, and participant 8 noted that "*it may lead to a low productivity in the environment*". Conversely, Yu (2025) and Biswas and Wang (2023) mentioned that there is a high demand for timely data processing and edge computing capabilities, considering the vast amount of data generated from these vehicles, and failure to implement them may result in network delays and ultimately threaten the safety of AVs. Guideline 4 is relevant and important as having immediate, accurate data is helpful for safe driving, especially with navigating between lanes and on and off highways.

Figure 6.6 reveals varying expert opinions regarding the difficulty of implementing this guideline. 40% of the participants neither agreed nor disagreed. Participant 4 added that "*It (guideline 4) will help the manufacturers for future models*". This observation shows uncertainty and underscores the need for further research to explore the implementation of real-time data processing mechanisms for future models.

The level of authority for guideline 4 is **Moderate Research Support (4)**. There is cumulative research support, and a significant majority (70%) of participants advocate for its inclusion in AV design and development and agree that its absence can lead to safety concerns. With only 20% of participants expressing an opposing viewpoint, consensus can be formed with continued research to solidify and refine this guideline. Adding to the rationale and description of this guideline, participant 9 mentioned that having immediate and accurate data is essential for safe driving and further supported that guideline 4 is mainly focused on addressing the 'big' issue of latency and getting immediate and accurate data. Table 7.4 presents the final formulation of guideline 4 (Real-time Data Processing), indicating the level of authority and revised title, description, and improved rationale. The improved rationale and description highlight views (in bold italics) from participants, emphasising the need for robust communication and immediate response.

Table 7.4: Refined presentation of Guideline 4

Guideline 4 (Real-Time Data Processing): Ensure robust V2X communication and Real-time data processing					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Integrate edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing, as the integration offers more advantages. The large amount of data collected through sensors and communication networks may increase the workload on the cloud and network delays, which hamper cloud computing and pose a risk to the system. ***There must be robust data processing algorithms to deal with large data and an immediate response requirement.***					
Rationale: Edge computing caters for applications with wireless communication requirements. It stores and processes massive amounts of data where it is generated to overcome any possible network delays. 5G supports highly interactive applications that are computationally intensive and have high quality of service (QoS) requirements. ***Additionally, immediate and accurate data is critical in ensuring effective communication to ensure human safety***					
References: Hassan, Yau and Wu, 2019; Sittón-Candanedo et al., 2019; Biswas and Wang, 2023; Pandharipande et al., 2023; Trapani and Longo, 2023					

7.2.3.5 *Guideline 5 (Legal and Moral Considerations)*

The object detection and classification, localisation, and the vehicular communication and real-time data processing tasks face ethical, legal, societal, and regulatory hurdles, primarily due to their involvement in acquiring data vulnerable to cybersecurity and privacy risks. These challenges can be mitigated by developing ethical and safety standards for AVs to incorporate ethical, legal, and societal aspects in AVs tailored to the local environment. From this, guideline 5 (ethical, legal, and societal considerations) is derived, which aims to strengthen research on ethical, legal, and societal issues for the improvement of safety and reliability. Guideline 5, as formulated in section 5.3, is about research on ethical, legal, and societal issues for the improvement of safety and reliability to develop relevant standards and legislation to address ethical and legal issues tailored to the South African region.

The results presented in section 6.5.2 and illustrated in Figure 6.7 show that participants agree to the relevance and significance of the guideline for improving AV perception. Furthermore, the majority (80%) of the participants agree that guideline 5 is important in the development of AV perception, with 10% of participants expressing disputing opinions. Consequently, participant 9 noted, "*it (guideline 5) would deal with mostly making control decisions"*. This aligns with the reviewed literature as presented in the rationale of this guideline, that the ethical standards will mainly help in making control decisions. However, AVs need ethical guidance on their interaction and communication with other vehicles and pedestrians. This further explains the results on whether guideline 5 addresses various factors that contribute to perception errors. Guideline 5 mainly addresses a critical part of AV perception, communication, which requires standards to guide data acquisition and sharing, and testing. This guideline primarily addresses factors related to AV decision and action layers. The reviewed literature also suggested the need for ethical, legal and societal considerations on the implementation of AI models and algorithms (Kshetri, 2020).

AV perception presents significant ethical challenges within the broader context of AV technology (Cunneen et al., 2020). The results in Figure 6.7 indicate that this guideline is difficult to implement. While Participant 9 acknowledges the importance of ethical considerations, they mentioned that it may take some time to work out how it can directly improve perception accuracy and reliability and added that failure to incorporate the guideline does not specifically impact AVs. Aligning with this, Participant 4 mentioned that *"It (guideline 5) will help improve future models"*.

The level of authority for guideline 5 is **Weak Research Support (3)**. There seems to be mixed agreement among experts' opinions on whether it should be applied in the design of the AV perception layer. While the majority (50%) of participants agreed, 20% disagreed, and a further 20% indicated uncertainty. This indicates that variability exists in the absolute necessity of its application, necessitating more research on the reasons behind their ratings. This is supported by Participant 4, who mentioned that "*more research will help"*, indicating that further research is imperative in this area for effective application. Furthermore, there is limited research-based support for this guideline.

In conclusion, the overall results agree with the literature on the effectiveness of guideline 5 in improving AV perception. However, a proportion of participants question how it would do that, as it mainly deals with control decisions. Nevertheless, literature shows the need for this guideline in ensuring that AV communication complies with relevant privacy laws and human rights, and AI algorithms also abide by these laws. Table 7.5 presents the final formulation of guideline 5 (Legal and Moral Considerations), indicating the level of authority and revised title to include ethics, as it is at the centre of this guideline and provides more meaning to the guideline.

Table 7.5: Refined presentation of Guideline 5

GUIDELINE 5 (ETHICAL, LEGAL, AND SOCIETAL CONSIDERATION): ADDRESS ETHICAL, LEGAL, AND SOCIETAL ISSUES THAT AFFECT AV PERCEPTION					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Strengthen research on ethical, legal, and societal issues for the improvement of safety and reliability. Engage with ethicists, legal experts, and policymakers to develop relevant standards and legislation to address ethical and legal issues tailored to the South African region. The standards and legislation must account for real-world testing and AV deployment, and development. These ethical, legal, and societal considerations must be incorporated into the design of the AV perception layer.					
Rationale: AVs require a predetermined way of dealing with specific ethical, legal, and societal issues. The standards will mainly help in making control decisions. However, AVs need ethical guidance on their interaction and communication with other vehicles and pedestrians.					
References: Martínez-Díaz and Soriguera, 2018; Szűcs and Hézer, 2022; Su, 2023					

7.2.3.6 *Guideline 6 (Testing and Validation)*

The tasks detailed in Figure 7.3 are inherently prone to failure without thorough testing and validation of perception layer operations. These challenges can be mitigated by developing testing and validation recommendations and rigorously testing AVs, aiming to enhance the successful execution of these critical tasks. From this emerges guideline 6 (Testing and Validation). Guideline 6, as formulated in section 5.3, focuses on testing perception algorithms in real-world conditions or conditions that closely resemble reality, allowing the vehicle to learn more about various environments and scenarios.

The evaluation results indicate that all participants agreed on the relevance, importance, and significance of this guideline on improving perception layer accuracy. This indicates that it is crucial to test perception algorithms for improved and accurate perception. For the perception layer to effectively execute the tasks in section 7.2, participants made it clear that it requires intensive testing across various scenarios to ensure human safety. While acknowledging its financial implications, as stated by participant 2, testing is critical to ensure the AV functionalities work as intended. Data acquisition in real-world or close to the real-world scenarios can be difficult, but most of it can be accomplished and improved over time, as stated by Participant 9. The results in Figure 6.8 underscore the critical role of testing in AV perception, and failure to test AV perception algorithms may mislead the decision and action layers.

The results revealed that guideline 6 is considered to have a low degree of difficulty to implement, with only 20% of the participants indicating that it is difficult to implement. Agreeing with its difficulty to implement, participant 2 noted, *"(it) is difficult because of high costs"*. Participants 4 asserted that, *"Testing before releasing will help to make the model better"*. Participant 9 concurred with the assertion, suggesting that not testing components of the AV perception layer will lead to the commercialisation of flawed products that can potentially contribute to dangerous driving decisions and increased accidents. This shows the importance and criticality of testing AV perception algorithms regardless of financial implications. Failure to implement this guideline threatens AV safety as testing ensures the elimination of unnecessary flaws. Supporting this, Participant 8 mentioned that guideline 6 *"helps identify potential perception errors and refine system performance"*.

The level of authority for guideline 6 is **Strong Research Support (5**) – A strong consensus exists among participants, with only one expressing uncertainty. However, participant 4 acknowledged the necessity of guideline 6 and noted, *"without testing there will be a lot of flaws"*. Additionally, there is cumulative and compelling literature that supports the application of this guideline as it is at the forefront of ensuring minimal perception errors. Table 7.6 presents the final formulation of guideline 6 (Testing and Validation), indicating the level of authority and the revised rationale highlighting the criticality of testing (in bold italic).

Table 7.6: Refined presentation of Guideline 6

GUIDELINE 6 (TESTING AND VALIDATION): DEVELOP AND TEST PERCEPTION ALGORITHMS UNDER CONDITIONS VERY CLOSE TO REALITY					
Level of Authority	**1**	**2**	**3**	**4**	**5**

Description: Rigorously test perception algorithms in real-world conditions or conditions that are very close to reality, as they enable the vehicle to learn more about different environments and scenarios. Precautionary measures must be taken to ensure human safety. Advanced algorithms must be used for environment mapping, and redundant systems must be employed to cross-verify environmental data.
Rationale: Extensive testing can help identify potential perception errors and refine the system's performance. Real-world testing, visual testing, simulation, and validation against ground truth data can help identify and reduce the risks of perception errors. ***Failure to test AV perception algorithms may mislead the decision and action layers.***
References: ISO 26262:2018; Rosique et al., 2019; Szűcs and Hézer, 2022; Pandharipande et al., 2023; Piazzoni et al., 2023

7.2.3.7 *Guideline 7 (Artificial Intelligence)*

Artificial Intelligence (AI) enables AVs to analyse and interpret data and provide the decision layer with accurate and real-time information (Kshetri, 2020; Boukerche and Sha, 2021). The performance of perception layer tasks, such as dynamic adaptation, object classification, vehicular communication and real-time feedback and motion forecasting, is significantly challenged by computational complexities and inadequate processing capabilities due to their need for continuous, timely updates. These limitations can be addressed by implementing AI algorithms that facilitate motion prediction and enhance self-learning capabilities, thereby improving the AV perception layer capabilities. From this, guideline 7 (Artificial Intelligence) is derived. Guideline 7, as formulated in section 5.3, is about training AI algorithms to recognise South Africa's unique road signs, environmental conditions, and driving behaviours, complying with relevant safety standards.

The results in Figure 6.9 indicate that AI is important and relevant to improving AV perception and reducing perception errors. Guideline 7 addresses various factors that can lead to perception errors. Participant 5 noted, "*This guideline must be applied in design*", emphasising that guideline 7 is essential in the design and development of the AV perception layer. Similarly, Participant 9 acknowledged AI's potential in managing large datasets while emphasising the challenges associated with its full implementation. Participant 4 also highlighted the importance of AI integration, while suggesting its implementation could be deferred to a later stage. Participant 4 further mentioned that *"AI will help the vehicle to learn what happens (around it)"*.

Participant 9 mentioned that the other requirements (Guidelines 1 - 6) are more important than AI. However, existing literature, as discussed in Section 4.6.1, suggested that AI can be used to support these guidelines (Guidelines 1 - 6). As a result, this study proposes the use of AI to support other requirements. It can be used effectively to:

- Train perception algorithms with greater precision,
- Improve sensor fusion techniques for enhanced integration,
- Enhance data processing mechanisms
- Assist in optimising sensor calibration.
- Facilitate dynamic adaptation within the AV perception layer.

The level of authority for guideline 7 is **Weak Research Support (3)**. Potentially, the level of authority for guideline 7 would be moderate as existing literature supports the application of this guideline in AV perception layer development, with established standards such as ISO 26262:2018, ISO/PAS 21448:2019, and PAS 1880:2020. However, there seems to be mixed agreement among participants' opinions on whether it must be applied in the design of AV perception. The results in Figure 6.9 indicated that 50% of participants generally agreed that it would be difficult to implement guideline 7. However, 30% seem unsure, with 10% disagreeing. While most participants agreed, the 30% that remained neutral show a level of uncertainty in their full application. This suggests that AI needs to be explored in the context of AV perception, aiming to mitigate challenges associated with its implementation. Table 7.7 presents the final formulation of guideline 7 (Artificial Intelligence), indicating the level of authority and improved rationale to emphasise the value of this guideline in supporting the other guidelines and changes are highlighted in bold italic.

Table 7.7: Refined presentation of Guideline 7

<table>
<tr><th colspan="6">GUIDELINE 7 (ARTIFICIAL INTELLIGENCE): UTILISE ARTIFICIAL INTELLIGENCE ALGORITHMS IN COMPLIANCE WITH SAFETY STANDARDS</th></tr>
<tr><td>Level of Authority</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td colspan="6">Description:
Train AI algorithms to recognise South Africa's unique road signs, environmental conditions, and driving behaviours. Artificial intelligence algorithms must comply with relevant safety standards and legislation. The data used in such algorithms must be accurate and representative of the real world. Use AI algorithms to support all other requirements (Guidelines 1-6).</td></tr>
</table>

Rationale: The use of AI systems, such as machine learning and deep learning, in AV perception can help the system to learn and improve over time. ***AI can be used to train perception algorithms with greater precision, improve sensor fusion techniques for enhanced integration, enhance data processing mechanisms, assist in optimising sensor calibration, and facilitate dynamic adaptation within the AV perception layer.***
References: ISO 26262:2018; Betz et al., 2019; ISO/PAS 21448:2019; Rosique et al., 2019; Fayyad et al., 2020; Yurtsever et al., 2020; Pas 1880:2020; Bachute and Subhedar, 2021; Biswas and Wang, 2023; Nahata and Othman, 2023; Sanjay and Yashwanth, 2023; Zakaria et al., 2023; Hurair, Ju and Han, 2024

7.3 Final Guidelines

Although most of the insights gained from the participants aligned with or strengthened the information (i.e. from literature) that formulated the preliminary guidelines, this section presents the final set of guidelines refined from the evaluation process.

Table 7.8: Final revised guidelines

GUIDELINE 1 (SENSOR FUSION): ESTABLISH ALGORITHMS FOR SENSOR FUSION IN AV PERCEPTION					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Develop and implement more advanced, robust, and precise sensor fusion algorithms that combine the large amount of data generated by individual sensors and related information in a unified format. The algorithms must synchronise all sensor data acquisitions based on a common timestamp to guarantee accurate interpretations.					
Rationale: The sensor fusion algorithms leverage the strengths of different sensors to overcome the limitations of individual sensors and enhance perception accuracy. The algorithms improve accuracy, reliability, and fault tolerance and decrease uncertainty in redundant data measurements. The integration of sensors could help address the challenge of object and lane detection in adverse weather conditions by providing a clear picture of the environment from different angles.					
References: Realpe, Vintimilla and Vlacic, 2016; Van Brummelen et al., 2018; Rosique et al., 2019; PAS 1880:2020; Wang, 2021; Dauptain et al., 2022; Hasanujjaman, Chowdhury and Jang, 2023; Nahata and Othman, 2023; Oudeif, Mohsen and Alasry, 2024					
GUIDELINE 2 (SENSOR CALIBRATION AND MAINTENANCE): REGULARLY CALIBRATE AND MAINTAIN THE VEHICLE SENSORS					
Level of Authority	**1**	**2**	**3**	**4**	**5**

Description: Constantly improve and update sensors to help reduce errors caused by sensor drift and degradation. Develop sensor cleaning strategies to cope with adverse weather conditions.
Rationale: Sensor calibration and maintenance requirements are crucial for sensor fusion and implementing algorithms for obstacle detection, localisation, and mapping. Regular maintenance and updates may help to address any potential issues and keep the perception system up to date. ***Rigorously tested sensor calibration and maintenance mechanisms can help minimise perception errors, ensuring human safety.***
References: ISO/PAS 21448:2019; Yeong et al., 2021; Dauptain et al., 2022; Kumar et al., 2022; Su, 2023

GUIDELINE 3 (FAULT TOLERANCE): ENSURE THE PERCEPTION SYSTEM IS ABLE TO RECOVER FROM ERRORS					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Additional sensor coverage should be considered to ensure safe and secure AV operations. This can be achieved by installing additional sensors. The implementation of a fault-tolerant system must be able to detect the error, discover the error location, and recover from the detected error.					
Rationale: The degradation or loss of a single sensor can make it necessary to bring the vehicle to a stop or cause safety issues. It is necessary to have measures in place for AVs to learn to operate in the presence of faults to avoid unplanned behaviours, especially those resulting from sensor faults.					
References: Realpe, Vintimilla and Vlacic, 2016; Pas 1880:2020; Zhao et al., 2024					

GUIDELINE 4 (REAL-TIME DATA PROCESSING): ENSURE ROBUST V2X COMMUNICATION AND REAL-TIME DATA PROCESSING					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Integrate edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing, as the integration offers more advantages. The large amount of data collected through sensors and communication networks may increase the workload on the cloud and network delays, which hamper cloud computing and pose a risk to the system. ***There must be robust data processing algorithms to deal with large data and an immediate response requirement.***					
Rationale: Edge computing caters for applications with wireless communication requirements. It stores and processes massive amounts of data where it is generated to overcome any possible network delays. 5G supports highly interactive applications that are computationally intensive and have high quality of service (QoS) requirements. ***Additionally, immediate and accurate data is critical in ensuring effective communication to ensure human safety.***					
References:					

Hassan, Yau and Wu, 2019; Sittón-Candanedo et al., 2019; Biswas and Wang, 2023; Pandharipande et al., 2023; Trapani and Longo, 2023

GUIDELINE 5 (ETHICAL, LEGAL, AND SOCIETAL CONSIDERATION): ADDRESS ETHICAL, LEGAL, AND SOCIETAL ISSUES THAT AFFECTS AV PERCEPTION

Level of Authority	**1**	**2**	**3**	4	5

Description:

Strengthen research on ethical, legal, and societal issues for the improvement of safety and reliability. Engage with ethicists, legal experts, and policymakers to develop relevant standards and legislation to address ethical and legal issues tailored to the South African region. The standards and legislation must account for real-world testing and AV deployment, and development. These ethical, legal, and societal considerations must be incorporated into the design of the AV perception layer.

Rationale:

AVs require a predetermined way of dealing with specific ethical, legal, and societal issues. The standards will mainly help in making control decisions. However, AVs need ethical guidance on their interaction and communication with other vehicles and pedestrians.

References:

Martínez-Díaz and Soriguera, 2018; Szűcs and Hézer, 2022; Su, 2023

GUIDELINE 6 (TESTING AND VALIDATION): DEVELOP AND TEST PERCEPTION ALGORITHMS UNDER CONDITIONS VERY CLOSE TO REALITY

Level of Authority	**1**	**2**	**3**	**4**	**5**

Description:

Rigorously test perception algorithms in real-world conditions or conditions that are very close to reality, as they enable the vehicle to learn more about different environments and scenarios. Precautionary measures must be taken to ensure human safety. Advanced algorithms must be used for environment mapping, and redundant systems must be employed to cross-verify environmental data.

Rationale:

Extensive testing can help identify potential perception errors and refine the system's performance. Real-world testing, visual testing, simulation, and validation against ground truth data can help identify and reduce the risks of perception errors. ***Failure to test AV perception algorithms may mislead the decision and action layers.***

References:

ISO 26262:2018; Rosique et al., 2019; Szűcs and Hézer, 2022; Pandharipande et al., 2023; Piazzoni et al., 2023

GUIDELINE 7 (ARTIFICIAL INTELLIGENCE): UTILISE ARTIFICIAL INTELLIGENCE ALGORITHMS IN COMPLIANCE WITH SAFETY STANDARDS

Level of Authority	**1**	**2**	**3**	4	5

Description:

Train AI algorithms to recognise South Africa's unique road signs, environmental conditions, and driving behaviours. Artificial intelligence algorithms must comply with relevant safety standards and legislation. The data used

in such algorithms must be accurate and representative of the real world. Use AI algorithms to support all other requirements (Guidelines 1-6).
Rationale: The use of AI systems, such as machine learning and deep learning, in AV perception can help the system to learn and improve over time. ***AI can be used to train perception algorithms with greater precision, improve sensor fusion techniques for enhanced integration, enhance data processing mechanisms, assist in optimising sensor calibration, and facilitate dynamic adaptation within the AV perception layer.***
References: ISO 26262:2018; Betz et al., 2019; ISO/PAS 21448:2019; Rosique et al., 2019; Fayyad et al., 2020; Yurtsever et al., 2020; Pas 1880:2020; Bachute and Subhedar, 2021; Biswas and Wang, 2023; Nahata and Othman, 2023; Sanjay and Yashwanth, 2023; Zakaria et al., 2023; Hurair, Ju and Han, 2024

7.4 Summary

This chapter outlined perception layer tasks and further discussed them to ensure the proposed guidelines are relevant to support the functionalities of the perception layer. The reviewed literature revealed seven fundamental perception layer tasks: Object Detection and Classification, Lane Detection and Tracking, Real-Time Feedback, Assess Potential Obstacles, Sensor Data Fusion, Dynamic Adaptation, and Localisation. Furthermore, four tasks emerged during the evaluation process: Motion Forecasting, Safety Systems Integration, Free Space Detection, and Weather Condition Detection and Response, which were discussed in this chapter. The evaluation process informed the refinement of the '*Real-Time Feedback*' task to '*Vehicular Communication and Real-Time Data Processing*'.

This chapter further discusses the preliminary guidelines leading to the revised set of guidelines. No new requirements were revealed from the evaluation process; rather, participants validated the preliminary guidelines while giving critical feedback where necessary. The evaluation feedback helped establish the level of authority for each guideline. Furthermore, the titles of guidelines 4 and 5 were revised to provide clarity and greater meaning. Where necessary, the description and rationale for specific guidelines were also revised to incorporate valuable insights from evaluation feedback. The final set of guidelines has been presented in this chapter.

Chapter 8: Conclusion, Limitations, and Recommendations

8.1 Introduction

This chapter provides an overview of the study and reflects on the process undertaken to address the main research question of this study. This chapter discusses how the research questions were achieved and presents the final set of guidelines. Furthermore, it provides a discussion on the theoretical and practical contributions of this study. Finally, this chapter acknowledges limitations of this study and provides recommendations for future research directions.

8.2 Research Overview

The study provides a set of guidelines that can be applied to minimise perception errors in autonomous vehicles (AVs). The research problem and objectives were discussed in Chapter 1 to underscore the necessity of these guidelines. Chapter 2 discussed the research methodology that guided the development of the guidelines. The process of developing these guidelines commenced with a thorough literature review presented in Chapters 3 – 5. Chapter 3 provides a foundational overview of AVs, including their system architecture (AVSA) and the critical role of the perception layer within the AVSA. Chapter 4 discusses the challenges that contribute to perception errors and hinder the development of fully automated vehicles. Additionally, it explores the potential enablers for mitigating these challenges. Drawing on insights from Chapters 3 and 4, Chapter 5 presents a set of preliminary guidelines. These guidelines were further evaluated through questionnaires (Chapter 6) to strengthen the learning from the literature. Section 2.2.1 provides how these chapters address the research sub-questions.

8.2.1 Achievements of Research Objectives

The study aimed to address the main research question of this study, formulated as *'How can perception errors be reduced in Autonomous Vehicle System Architecture to improve safety and limit technical challenges?'*. To achieve this objective, the study addressed the following research sub-questions:

RSQ1: What should be the key tasks of the perception layer of the Autonomous Vehicles System Architecture?

RSQ1 primarily aims to provide an understanding of the overall role of the perception layer in the AV system architecture, serving as a basis for answering the main research question of this study. Chapter 3 defined AVs and the AVSA, and provided the two key components (i.e., sensors and vehicular communication) of the perception layer of AVs, building up to answer RSQ1. Chapter 3 discussed how the AV perception layer interacts with other AV layers and the surrounding environment. The chapter finally discussed and elaborated on the perception layer tasks that were discovered from the reviewed literature. The literature reviewed in this study revealed seven perception layer tasks and the importance of each one of them. The discovered tasks are as follows: object detection and classification, lane detection and tracking, providing real-time updates and feedback, potential obstacles assessment, sensor data fusion, dynamic adaptation, and localisation. In addition, a questionnaire (Chapter 6) was administered to experts to review and evaluate the importance of the discovered perception layer tasks. The expert review process revealed the following four tasks in addition to the seven from the literature: motion forecasting, safety systems integration, free space detection, and weather condition detection and response.

RSQ2: What are the technical enablers and challenges encountered in autonomous vehicles?

RSQ2 aimed to uncover AV perception challenges, particularly in South Africa, that can lead to perception errors. To address this question, key challenges were discovered in chapter 4 as: sensor limitations and failures, environmental factors and road infrastructure, computation complexity and processing requirements, as well as ethical, legal and societal challenges. Chapter 4 further elaborates on these challenges and how they hinder the development or deployment of AVs in South Africa. Another part of the question was aimed at finding technical enablers as a base to develop the final guidelines of this study. These enablers were discussed in Chapter 4. Table 4.1 provides a summary of the challenges and potential requirements that can assist in mitigating the problem.

RSQ3: What guidelines could be followed to reduce perception errors in the Autonomous Vehicle System Architecture?

RSQ3 builds on RSQ1 and RSQ2, aiming to provide potential guidelines to be followed in minimising perception errors. To achieve this, Chapter 5 developed seven guidelines with descriptions and their rationale, aiming to answer RSQ3. These guidelines were further evaluated by experts through an online questionnaire, and the results were presented in Chapter 6. The overall results proved the importance and effectiveness of these guidelines in solving the research problem. The questionnaire results were used to inform the final set of guidelines that are presented in section 7.3.

8.3 Research Contribution

The contribution of this study includes the key perception tasks of the AV perception layer. Figure 8.1 below shows the key perception tasks incorporating the emergent tasks (all highlighted in red) from the evaluation process.

Figure 8.1: Final Perception Layer Tasks

However, the main contribution of the study presented below in Table 8.1 is the final set of guidelines, which answers the main research question of this study, formulated as:

How can perception errors be reduced in Autonomous Vehicle System Architecture to improve safety and limit technical challenges?

Table 8.1: Final Guidelines

GUIDELINE 1 (SENSOR FUSION): ESTABLISH ALGORITHMS FOR SENSOR FUSION IN AV PERCEPTION					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Develop and implement more advanced, robust, and precise sensor fusion algorithms that combine the large amount of data generated by individual sensors and related information in a unified format. The algorithms must synchronise all sensor data acquisitions based on a common timestamp to guarantee accurate interpretations.					
Rationale: The sensor fusion algorithms leverage the strengths of different sensors to overcome the limitations of individual sensors and enhance perception accuracy. The algorithms improve accuracy, reliability, and fault tolerance and decrease uncertainty in redundant data measurements. The integration of sensors could help address the challenge of object and lane detection in adverse weather conditions by providing a clear picture of the environment from different angles.					
References: Realpe, Vintimilla and Vlacic, 2016; Van Brummelen et al., 2018; Rosique et al., 2019; PAS 1880:2020; Wang, 2021; Dauptain et al., 2022; Hasanujjaman, Chowdhury and Jang, 2023; Nahata and Othman, 2023; Oudeif, Mohsen and Alasry, 2024					
GUIDELINE 2 (SENSOR CALIBRATION AND MAINTENANCE): REGULARLY CALIBRATE AND MAINTAIN THE VEHICLE SENSORS					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Constantly improve and update sensors to help reduce errors caused by sensor drift and degradation. Develop sensor cleaning strategies to cope with adverse weather conditions.					
Rationale: Sensor calibration and maintenance requirements are crucial for sensor fusion and implementing algorithms for obstacle detection, localisation, and mapping. Regular maintenance and updates may help to address any potential issues and keep the perception system up to date. Rigorously tested sensor calibration and maintenance mechanisms can help minimise perception errors, ensuring human safety.					
References: ISO/PAS 21448:2019; Yeong et al., 2021; Dauptain et al., 2022; Kumar et al., 2022; Su, 2023					
GUIDELINE 3 (FAULT TOLERANCE): ENSURE THE PERCEPTION SYSTEM IS ABLE TO RECOVER FROM ERRORS					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description:					

Additional sensor coverage should be considered to ensure safe and secure AV operations. This can be achieved by installing additional sensors. The implementation of a fault-tolerant system must be able to detect the error, discover the error location, and recover from the detected error.

Rationale:

The degradation or loss of a single sensor can make it necessary to bring the vehicle to a stop or cause safety issues. It is necessary to have measures in place for AVs to learn to operate in the presence of faults to avoid unplanned behaviours, especially those resulting from sensor faults.

References:

Realpe, Vintimilla and Vlacic, 2016; Pas 1880:2020; Zhao et al., 2024

Guideline 4 (Real-Time Data Processing): Ensure robust V2X communication and Real-time data processing

Level of Authority	1	2	3	4	5

Description:

Integrate edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing, as the integration offers more advantages. The large amount of data collected through sensors and communication networks may increase the workload on the cloud and network delays, which hamper cloud computing and pose a risk to the system. There must be robust data processing algorithms to deal with large data and an immediate response requirement.

Rationale:

Edge computing caters for applications with wireless communication requirements. It stores and processes massive amounts of data where it is generated to overcome any possible network delays. 5G supports highly interactive applications that are computationally intensive and have high quality of service (QoS) requirements. Additionally, immediate and accurate data is critical in ensuring effective communication to ensure human safety

References:

Hassan, Yau and Wu, 2019; Sittón-Candanedo et al., 2019; Biswas and Wang, 2023; Pandharipande et al., 2023; Trapani and Longo, 2023

Guideline 5 (Ethical, Legal, and Societal consideration): Address ethical, legal, and societal issues that affects AV perception

Level of Authority	1	2	3	4	5

Description:

Strengthen research on ethical, legal, and societal issues for the improvement of safety and reliability. Engage with ethicists, legal experts, and policymakers to develop relevant standards and legislation to address ethical and legal issues tailored to the South African region. The standards and legislation must account for real-world testing and AV deployment, and development. These ethical, legal, and societal considerations must be incorporated into the design of the AV perception layer.

Rationale:

AVs require a predetermined way of dealing with specific ethical, legal, and societal issues. The standards will mainly help in making control decisions. However, AVs need ethical guidance on their interaction and communication with other vehicles and pedestrians.					
References: Martínez-Díaz and Soriguera, 2018; Szűcs and Hézer, 2022; Su, 2023					
GUIDELINE 6 (TESTING AND VALIDATION): DEVELOP AND TEST PERCEPTION ALGORITHMS UNDER CONDITIONS VERY CLOSE TO REALITY					
Level of Authority	**1**	**2**	**3**	**4**	**5**
Description: Rigorously test perception algorithms in real-world conditions or conditions that are very close to reality, as they enable the vehicle to learn more about different environments and scenarios. Precautionary measures must be taken to ensure human safety. Advanced algorithms must be used for environment mapping, and redundant systems must be employed to cross-verify environmental data.					
Rationale: Extensive testing can help identify potential perception errors and refine the system's performance. Real-world testing, visual testing, simulation, and validation against ground truth data can help identify and reduce the risks of perception errors. Failure to test AV perception algorithms may mislead the decision and action layers.					
References: ISO 26262:2018; Rosique et al., 2019; Szűcs and Hézer, 2022; Pandharipande et al., 2023; Piazzoni et al., 2023					
GUIDELINE 7 (ARTIFICIAL INTELLIGENCE): UTILISE ARTIFICIAL INTELLIGENCE ALGORITHMS IN COMPLIANCE WITH SAFETY STANDARDS					
Level of Authority	**1**	**2**	**3**	4	5
Description: Train AI algorithms to recognise South Africa's unique road signs, environmental conditions, and driving behaviours. Artificial intelligence algorithms must comply with relevant safety standards and legislation. The data used in such algorithms must be accurate and representative of the real world. Use AI algorithms to support all other requirements (Guidelines 1-6).					
Rationale: The use of AI systems, such as machine learning and deep learning, in AV perception can help the system to learn and improve over time. AI can be used to train perception algorithms with greater precision, improve sensor fusion techniques for enhanced integration, enhance data processing mechanisms, assist in optimising sensor calibration, and facilitate dynamic adaptation within the AV perception layer.					
References: ISO 26262:2018; Betz et al., 2019; ISO/PAS 21448:2019; Rosique et al., 2019; Fayyad et al., 2020; Yurtsever et al., 2020; Pas 1880:2020; Bachute and Subhedar, 2021; Biswas and Wang, 2023; Nahata and Othman, 2023; Sanjay and Yashwanth, 2023; Zakaria et al., 2023; Hurair, Ju and Han, 2024					

8.3.1 Theoretical Contribution

The study employs design science to contribute to the knowledge base through the development of guidelines that can be used by AV engineers and developers in the design and development of AVs, aiming to minimise perception errors. This contribution is achieved through a two-phase approach detailed in section 2.7.

In Phase 1, a comprehensive review of relevant literature established the theoretical foundation (Chapters 3 & 4) for developing the preliminary guidelines. The output was presented in Chapter 5 as the preliminary guidelines (Chapter 5).

Phase 2 involved the review and evaluation of the preliminary guidelines through questionnaires to inform the final guidelines (Chapter 6). The study used the Framework for Evaluating Design Science Research (FEDS) to assess the rigour, relevance and effectiveness of the preliminary guidelines informing the development of the final, refined set of guidelines.

8.3.2 Practical Contribution

AVs are emerging within the South African context. Although South Africa continues to learn from international best practices, there is a need for solutions tailor-made for South African transport and related problems. The study contributes a set of guidelines that can be used for the design and development of AVs to solve South African problems relating to AVs, with a particular focus on mitigating perception errors. These guidelines aim to provide AV engineers and developers with key requirements that can be practically explored to develop more reliable and safe AVs operating within the South African environment.

8.4 Limitations

The limitations of this study include:

- The evaluation method (questionnaires) used in this study limited the ability of the researcher to interact with the participants to prompt additional information and clarity on their responses. A more interactive method, such as in-depth interviews, would have provided richer insights.
- The requirements used to develop guidelines were defined based on the literature reviewed by the researcher. The researcher does acknowledge that it is plausible that more requirements may be discovered beyond the scope of this study.

- South Africa is an emerging market for AVs. Consequently, the researcher acknowledges that there may be a possible dearth of in-depth knowledge on their design and development.

8.5 Future Research

The guidelines provided in this study need to be explored to determine technical strategies on how they can be implemented. Furthermore, future research can focus more on the environmental factors and road infrastructure conditions affecting AVs, as this is beyond the scope of this study. Another direction could be addressing factors that could affect the decision and action layers of the autonomous vehicle system architecture. Additionally, future research with a larger qualitative component could further explore the guidelines identified in this study. Finally, there is a need for AV adoption solutions and strategies tailored for the South African context.

8.6 Personal Reflection

The research process for my thesis has been a profoundly transformative experience, pushing the boundaries of my understanding and resilience. Addressing the complexities of such a topic based on real-world challenges in an emerging market was difficult, often leading to frustration when solutions were not immediately apparent. The overall research journey has been a profound journey of growth, stretching me in ways I hadn't anticipated. It was undeniably difficult at times; there were moments when the sheer amount of information felt overwhelming, the demands of academic rigour challenged me greatly, and discouraging words about the 'difficulty' of this research potentially affected me. The journey was undoubtedly filled with challenges. I even recall a particular period when I fell physically ill, necessitating a trip home away from campus to recuperate. That time away, while frustrating, surprisingly offered a new perspective and renewed my determination. Through these challenges, I've cultivated invaluable skills and lessons. The primary solution I embraced was the power of iterative refinement – understanding that initial approaches would rarely be perfect and that continuous adaptation was key to developing robust guidelines. I have learned the invaluable lesson of resilience – that perseverance, faith, and adaptability are just as important as intellectual ability. I have also sharpened my problem-solving skills, learning to break down complex issues into manageable parts and to critically evaluate sources for a deeper understanding.

Looking back, the personal significance of this achievement is immense. As the first in my family to reach this level of study, there's an overwhelming sense of pride, not only for myself but for my entire family. Their support has been unwavering, and their pride is evident. My mother, in particular, made countless sacrifices to ensure I had the opportunities to pursue my education and career aspirations. Her faith and dedication are a constant source of inspiration, highlighting the profound impact of this journey beyond simple academic attainment. The skills of critical thinking, meticulous organisation, and effective communication are lessons I will carry with me, not only in future academic pursuits but in every aspect of my life and career.

8.7 Summary

The study aimed at developing guidelines focused on minimising perception errors in autonomous vehicles. The development of these guidelines followed the Design Science Research Methodology process. The design of these guidelines was based on key requirements discovered from literature and expert reviews. The research sub-questions guided this study to address the main research question and the literature review process. RSQ1 provided an understanding of the overall role of the perception layer in the AV system architecture. RSQ2 uncovered AV perception challenges, particularly in the South African context. RSQ3 provided potential guidelines to be followed in minimising perception errors. The expert reviewers assisted in determining whether the guidelines address the research problem and solve real-life problems. The insights from the expert review process were used to strengthen the preliminary guidelines, informing a final set of guidelines.

In this chapter, the researcher reflects on the research journey and how each of the research sub-questions was addressed. The chapter provided the value of this study, limitations and potential directions for future research.

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Appendix A: Differences between deductive, inductive and abductive research approaches (adapted from Saunders, Lewis and Thornhill, 2019)

	Deduction	Induction	Abduction
Logic	In a deductive inference, when the premises are true the conclusion must also be true	In an inductive inference, known premises are used to generate untested conclusions.	In an abductive inference, known premises are used to generate testable conclusions.
Generalisability	Generalise from the general to the specific.	Generalise from the specific to the general.	Data collection is used to explore a phenomenon, identify themes and patterns, locate these in a conceptual framework, and test this through subsequent data collection.
Use of data	Data collection is used to evaluate propositions or hypotheses related to an existing theory.	Data collection is used to explore a phenomenon, identify themes and patterns, and create a conceptual framework	Data collection is used to explore a phenomenon, identify themes and patterns, locate these in a conceptual framework, and test this through subsequent data collection.
Theory	Theory falsification or verification.	Theory generation and building.	Theory generation or modification; incorporating existing theory where appropriate to build new theory or modify existing theory.

Appendix B: Ethical Clearance Letter

Rhodes University Human Research Ethics Committee
Main Admin Building, Drostdy Road, Makhanda, 6139, South Africa
PO Box 94, Makhanda, 6140, South Africa
t: +27 (0) 46 603 7314
e: ethics-committee@ru.ac.za
https://www.ru.ac.za/researchgateway/ethics/
NHREC Registration number: RC-241114-045

14 August 2024

Mr Itumeleng Ramala

Email: ramalaitu27@gmail.com

Review Reference: 2024-7646-8988

Dear Mr Ramala,

Re: Guidelines for reducing perception errors in Autonomous Vehicle System Architecture

Researcher: Mr Itumeleng Ramala

Supervisor(s): Dr Monelo Nxozi

This letter confirms that the above research proposal has been reviewed by the Rhodes University Human Research Ethics Committee (RU-HREC) and **PROVISIONALLY APPROVED PENDING PERMISSION/GATEKEEPER LETTER(S)**.

Gatekeeper permission is required from:

[redacted]

Once the Gatekeeper permission letter/s has been received please forward it to the Ethics Coordinator, in order to finalize your ethics approval.

If your study also involves participants who do not need gatekeeper permission because they are participating in their individual capacity, and you would like to commence data collection with these participants, you may apply to the committee for Partial Approval to do so. Email your request to ethics-committee@ru.ac.za.

Sincerely,

Janet Hayward

Dr Janet Hayward

Chair: Rhodes University Human Research Ethics Committee, RU-HREC

cc: Ethics Coordinator

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Appendix C: Expert Review Questionnaire

SECTION A: AUTONOMOUS VEHICLES PERCEPTION LAYER TASKS
Note to respondent: The following questions relate to the **research sub-question 1** *RSQ1: What should be the key tasks of the perception layer of the Autonomous Vehicles System Architecture?*

Based on your knowledge, rate the importance of the following AV perception layer tasks:	Not Important	Slightly Important	Moderately Important	Important	Very Important
1. Object Detection and Classification					
2. Lane Detection and Tracking					
3. Real-Time Feedback					
4. Assess Potential Obstacles					
5. Sensor Data Fusion					
6. Dynamic Adaptation					
7. Localization					

Please provide any additional tasks of the perception layer:

SECTION B: Proposed Guidelines Evaluation

Note to respondent: The following questions relate to the proposed safety guidelines, as well as research sub-question 2 and sub-question 3
RSQ2: *What are the technical enablers and challenges encountered in autonomous vehicles?*
RSQ3: *What guidelines could be followed to reduce perception errors in the Autonomous Vehicle System Architecture?*

Guideline 1 (Sensor Fusion): Establish algorithms for sensor fusion in AV perception.

Description:

Develop and implement more advanced, robust, and precise sensor fusion algorithms that combine the large amount of data generated by individual sensors and related information in a unified format. The algorithms must synchronise all sensor data acquisitions based on a common timestamp to guarantee accurate interpretations.

Rationale:

The sensor fusion algorithms leverage the strengths of different sensors to overcome the limitations of individual sensors and enhance perception accuracy. The algorithms improve accuracy, reliability, and fault tolerance and decrease uncertainty in redundant data measurements. The integration of sensors could help address the challenge of object and lane detection in adverse weather conditions by providing a clear picture of the environment from different angles.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
8. This guideline is relevant to improving autonomous vehicles perception?					

9. This guideline is an important autonomous vehicle perception layer development practice?					
10. This guideline addresses various factors contributing to perception errors in autonomous vehicles?					
11. This guideline has a significant impact on improving perception accuracy and reliability?					
12. This guideline must be applied in design?					
13. This guideline is difficult to implement in the development of the AV perception layer?					
14. Failure to incorporate this guideline has a negative impact on the development of autonomous vehicles' perception accuracy and reliability?					

Please provide any additional comments:

Guideline 2 (Sensor Calibration and Maintenance): Regularly calibrate and maintain the vehicle sensors.

Description:

Constantly improve and update sensors to help reduce errors caused by sensor drift and degradation. Develop sensor cleaning strategies to cope with adverse weather conditions.

Rationale:

Sensor calibration and maintenance requirements are crucial for sensor fusion and implementing algorithms for obstacle detection, localization, and mapping. Regular maintenance and updates may help to address any potential issues and keep the perception system up to date.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
11. This guideline is relevant to improving autonomous vehicles perception?					
12. This guideline is an important autonomous vehicle perception layer development practice?					
13. This guideline addresses various factors contributing to perception errors in autonomous vehicles?					
14. This guideline has a significant impact on improving perception accuracy and reliability?					
15. This guideline must be applied in design?					
16. This guideline is difficult to implement in the development of the AV perception layer?					
17. Failure to incorporate this guideline has a negative impact on the development of autonomous vehicles' perception accuracy and reliability?					

Please provide any additional comments:

Guideline 3 (Fault tolerance): Ensure the perception system is able to recover from errors.

Description:

Additional sensor coverage should be considered to ensure safe and secure AV operations. This can be achieved by installing additional sensors. The implementation of a fault-tolerant system must be able to detect the error, discover the error location, and recover from the detected error.

Rationale:

The degradation or loss of a single sensor can make it necessary to bring the vehicle to a stop or cause safety issues. It is necessary to have measures in place for AVs to learn to operate in the presence of faults to avoid unplanned behaviours, especially those resulting from sensor faults.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
18. This guideline is relevant to improving autonomous vehicles perception?					
19. This guideline is an important autonomous vehicle perception layer development practice?					
20. This guideline addresses various factors contributing to perception errors in autonomous vehicles?					
21. This guideline has a significant impact on improving perception accuracy and reliability?					

22. This guideline must be applied in design?					
23. This guideline is difficult to implement in the development of the AV perception layer?					
24. Failure to incorporate this guideline has a negative impact on the development of autonomous vehicles' perception accuracy and reliability?					

Please provide any additional comments:

Guideline 4 (Real-time data processing): Ensure robust V2X communication

Description:

Integrate edge computing and 5G for low latency and higher throughput instead of cloud computing for real-time data processing, as the integration offers more advantages. The large amount of data collected through sensors and communication networks may increase the workload on the cloud and network delays, which hamper cloud computing and pose damage to the system.

Rationale:

Edge computing caters for applications with wireless communication requirements. It stores and processes massive amounts of data where it is generated to overcome any possible network delays. 5G supports highly interactive applications that are computationally intensive and have high quality of service (QoS) requirements

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
25. This guideline is relevant to improving autonomous vehicles perception?					
26. This guideline is an important autonomous vehicle perception layer development practice?					
27. This guideline addresses various factors contributing to perception errors in autonomous vehicles?					
28. This guideline has a significant impact on improving perception accuracy and reliability?					
29. This guideline must be applied in design?					
30. This guideline is difficult to implement in the development of the AV perception layer?					
31. Failure to incorporate this guideline has a negative impact on the development of autonomous vehicles' perception accuracy and reliability?					

Please provide any additional comments:

Guideline 5 (Legal and moral consideration): Address ethical, legal and societal issues

Description:

Strengthen research on ethical, legal, and societal issues for improvement of safety and reliability. Engage with ethicists, legal experts, and policymakers to develop relevant standards and legislation to address ethical and legal issues tailored to the South African region. The standards and legislation must account for real-world testing and AV deployment and development. These ethical, legal, and societal considerations must be incorporated into the design of the AV perception layer.

Rationale:

AVs require a predetermined way of dealing with specific ethical, legal, and societal issues. The standards will mainly help in making control decisions. However, AVs need ethical guidance on the interaction and communication with other vehicles and pedestrians

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
32. This guideline is relevant to improving autonomous vehicle perception?					
33. This guideline is an important autonomous vehicle perception layer development practice?					
34. This guideline addresses various factors contributing to perception errors in autonomous vehicles?					

35. This guideline has a significant impact on improving perception accuracy and reliability?					
36. This guideline must be applied in design?					
37. This guideline is difficult to implement in the development of the AV perception layer?					
38. Failure to incorporate this guideline has a negative impact on the development of autonomous vehicles' perception accuracy and reliability?					

Please provide any additional comments:

Guideline 6 (Testing and Validation): Develop and test the perception algorithms under conditions very close to reality.

Description:

Rigorously test perception algorithms in real-world conditions or conditions that are very close to reality as they enable the vehicle to learn more about different environments and scenarios. Precautionary measures must be taken to ensure human safety. Advanced algorithms must be used for environment mapping, and redundant systems must be employed to cross-verify environmental data.

Rationale:

Extensive testing can help identify potential perception errors and refine the system's performance. Real-world testing, visual testing, simulation, and validation against ground truth data can help identify and reduce the risks of perception errors.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
39. This guideline is relevant to improving autonomous vehicle perception?					
40. This guideline is an important autonomous vehicle perception layer development practice?					
41. This guideline addresses various factors contributing to perception errors in autonomous vehicles?					
42. This guideline has a significant impact on improving perception accuracy and reliability?					
43. This guideline must be applied in design?					
44. This guideline is difficult to implement in the development of the AV perception layer?					
45. Failure to incorporate this guideline has a negative impact on the development of autonomous vehicles' perception accuracy and reliability?					

Please provide any additional comments:

Guideline 7 (Artificial Intelligence): Utilize artificial intelligence algorithms in compliance with safety standards

Description:

Train AI algorithms to recognise South Africa's unique road signs, environmental conditions, and driving behaviours. Artificial intelligence algorithms must comply with relevant safety standards and legislation. The data used in such algorithms must be accurate and representative of the real world. Use AI algorithms to support all other requirements (Guidelines 1-6).

Rationale:

The use of AI systems, such as machine learning and deep learning in AV perception, can help the system to learn and improve over time

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
46. This guideline is relevant to improving autonomous vehicle perception?					
47. This guideline is an important autonomous vehicle perception layer development practice?					
48. This guideline addresses various factors contributing to perception errors in autonomous vehicles?					

49. This guideline has a significant impact on improving perception accuracy and reliability?					
50. This guideline must be applied in design?					
51. This guideline is difficult to implement in the development of the AV perception layer?					
52. Failure to incorporate this guideline has a negative impact on the development of autonomous vehicles' perception accuracy and reliability?					

Please provide any additional comments (or additional guidelines/requirements if any):

Thank you for participants

End of Questionnaire

Appendix D: Published SAICIT Conference Paper

Below is the reference of the paper presented and published at the 45th Annual Conference of the South African Institute of Computer Scientists and Information Technologists (SAICIT) 2024:

'Ramala, I. and Nxozi, M., Guidelines for reducing perception errors in Autonomous Vehicle System Architecture. In *The 45th Annual Conference of the South African Institute of Computer Scientists and Information Technologists* (p. 16).'