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Reliability Analysis of the Functional Capabilities of an Autonomous Vehicle

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Abstract
The reliability of autonomous vehicles (AVs) is a research domain of high interest, covering a diverse pool of researchers, captains of smart auto industries, government agencies, and technology enthusiasts. The reliability of AVs is not extensively explored in the literature, despite the apprehension due to fatal accidents recorded in the past. Despite being in existence for over a decade, AVs have yet to reach a certified commercial-level deployment. Due to the complexity that comes with the self-operation of an AV, the issue of trustworthiness, which signifies reliability, becomes inevitable. The identification, analysis, and categorization of functional elements using systems engineering conceptual design principles and the linkage of these to the road traffic rules were conducted to address this. Also, the evaluation of the reliability of AVs using various developed vehicles from selected industries was addressed by integrating the traffic rules. The analysis of reliability was carried out using life-to-failure data premised on the probability plotting approach. It was found that there is a 99.94% chance that an autonomous vehicle will fail at least one of the traffic rules within 20 minutes of driving. Furthermore, the hazard rate of AVs was found to be on the rise, meaning a high indication of accidents.

Keywords- Autonomous vehicles, Functional capability, Physical embodiment, Reliability analysis, Systems engineering conceptual design.

1. Introduction

Autonomous vehicle (AV) performance in respect of adherence to traffic rules is still a major concern in the literature on self-driving robotic systems (Uzair, 2021). This is impacted by the functional capabilities of an AV, which mostly extend to questions related to its reliability. Grigorescu et al. (2020) and Chy et al. (2021) stated that the capabilities of Autonomous Vehicles (AVs) have over the years transformed and improved how scenarios along a driving route should be predicted, including reactions to complex, unknown, or unforeseen situations. Automotive industries involved with the planning, design, and manufacture of AVs, members of academia, researchers, and students in the fields of robotics, smart systems, reliability engineering, and government agencies, amongst others, are the main targets of this research. The concept of AVs and their development gradually advanced to some level of fame over two decades ago. The advancement of AVs was due to advances in artificial intelligence and its sub-organs, such as deep learning. The emerging technology that comes with AVs is complex and risky, spanning across *geopolitical* and *socio-economic* domains (Tan and Taeihagh, 2021). With this in consideration, any nation that chooses to introduce AVs may experience difficulties, especially among developing economies. This is based on the fact that most developing economies lack the Fourth Industrial Revolution (4IR) technology while the technology associated with AVs is getting much more advanced beyond the 4IR technology (Ndung'u and Signé, 2020). Hence, if there is a lack of technological competency, there will be issues with any AV developed in such societies. The inherent complexity of an

AV makes it difficult to comply with certain conditions within a certain period. This inherent complexity also makes it difficult for an AV to be deployed in certain societies.

One of the most notable problems facing today's AVs is the inherent operational and functional complexities that are orchestrated by the employed technology, which revolves around diverse-multiple interacting sensors, the need for real-time decision-making to avert bumpy rides, and mostly minimize or eliminate accidents. AVs are more involved in activities seen as complex as they try to imitate human dexterity in driving. These sets of actions require an AV to trigger itself and make quick, smart, and reliable decisions accurately and precisely.

According to Grigorescu et al. (2020) and Chy et al. (2021), AV research has over the years grown, especially in respect of how they predict situations and how they should react to complex and unknown situations or unforeseen situations. The improvements recorded were possible due to the method called *deep learning* or *smart deep learning* and the advancements of Artificial Intelligence (AI) technology and its applications. Given these advancements, it can be noted that there is good progress in the field of AVs, however, their reliability is still a problem, and there is little research regarding the reliability on the road.

Despite the recorded advances with AVs, situation prediction still poses a significant challenge in real-life scenarios. Decision-making by AVs depends on the method used to formulate their navigation strategies for various situations (Schwarting et al., 2018). By extension, the reliability of an AV's performance with respect to traffic rules is largely unknown. This makes it difficult to trust the technology that these vehicles rely on. No substantial evidence of reliability analysis is provided in the literature on AVs with respect to on-road autonomous navigation. Due to the questionable reliability of this emerging knowledge domain, the delay in commercializing AVs has been upheld as the issue of trustworthiness has remained in the spotlight.

The literature in the field of AVs has significantly grown over the years. In a bid to detect objects, Shelhamer et al. (2017) and Wu (2017) discussed the Convolutional Neural Network (CNN) approach as a promising real-time object detection tool. CNN can be defined as a multilayer neural network which can also be referred to as deep learning architecture and it makes use of Artificial Intelligence (AI) detective principles. The visual system of living beings inspired CNN as it is commonly used to analyze images (Ghosh et al., 2020). The use of a CNN-based approach was reviewed by Hnewa and Radha (2021). It was found that the CNN-based approach performed well in clear weather conditions in respect of object detection. However, rainy weather conditions yield less accurate detection of objects than clear weather conditions. However, this does not mean that the method does not work in rainy conditions. The problem that caused less accuracy in rainy conditions was the inability to detect and locate the objects as expected at some point. This is caused by the rain covering, which aids in obscuring the important details of the objects (Hnewa and Radha, 2021). The main performance metric used in the test is the Mean Average Precision (MAP) which is said to be the most popular performance measure since 2012.

Vaicenavicius et al. (2021) highlighted one important functional requirement, i.e., the ability of an AV to stop in a bid to avoid harm or danger. This requirement sums up a couple of requirements. Badue et al. (2021) surveyed a search on self-driving vehicles that focused on vehicles with the autonomous driving capability of level 3 and above. The study identified two main functional requirement categories: the perception system and the decision-making system of an autonomous vehicle. The perception system of a self-driving vehicle consists of the following functional requirements, (1) the vehicle should have different methods of localization via Light Detection and Ranging (LIDAR) based localization, LIDAR plus camera-based localization, and camera-based localization; (2) the vehicle should be able to map obstacles offline via regular spacing metric representation and varied spacing metric representation; (3) an AV should be able to conduct road mapping using metric representation and topological representation; (4) an AV should be able to track moving obstacles using traditional-based Ministry of Transport (MOT), model-based MOT, stereo vision based MOT, grid map based MOT, sensor fusion based MOT, deep learning based MOT and (5) an AV should be able to detect and recognize traffic signalization. These can be achieved by traffic light detection and recognition, traffic sign detection and recognition, and pavement marking detection and recognition.

General decision-making by AVs is still a source of concern and can be occasionally immature. AVs can plan how to behave or react in normal and sometimes complex situations. However, complex situations are usually more difficult to handle; hence, mistakes occur. Complex situations in decision-making come with a dynamic environment. The dynamic environment brings uncertainty to data acquisition handling. Data acquisition helps in understanding an environment in real-time to plan appropriately, to avoid dangerous situations. Data acquisition and analysis in real-time are still challenges (González et al., 2015).

In respect of decision-making for a self-driving vehicle, Badue et al. (2021) described the following functional requirements that a vehicle should be enabled to meet: (1) conduct route planning – the vehicle can achieve this by using the following techniques goal-directed, separator-based, hierarchical, and bounded-hop, or combining any of the techniques; (2) select its expected behavior – the techniques that can be adopted for this requirement are Finite State Machines (FSM) (Jo et al., 2015), ontology (Zhao et al., 2015; Zhao et al., 2017), and Markov decision process; (3) plan its motion – the motion planning consists of graph search, sampling, an interpolating curve such as clothoid curves (González et al., 2015), and numerical optimization techniques; (4) control its systems – the methods used for this are direct hardware actuation control and path tracking.

The identification of functional capabilities for AVs was discussed by Matthaei and Maurer (2015), Vaicenavicius et al. (2021) and Badue et al. (2021). The functional requirements are needed to make sure that the capabilities are met. These requirements speak to the AVs' intelligence; therefore, they are categorized into two main systems. The perception system—the vehicle should always know how to identify its environment, and the cognition system for decision-making, such as what the AV should do and how it should do it. Sviatov et al. (2021) described a structural and functional model of an autonomous vehicle control system, intending to generate several mathematical problems. Their study identified the control system of an autonomous vehicle as a functional requirement. This requirement refers to the vehicle being able to control itself. Other functional design structures include those developed by Badue et al. (2021), Guanetti et al. (2018) and Sell et al. (2018).

The study conducted by Guanetti et al. (2018) highlighted that decision-making and motion planning of Connected and Automated Vehicles (CAV) generated a reference trajectory for longitudinal and lateral motion. Therefore, the trajectory is expected to follow traffic rules, be feasible for lower-level controllers, and be comfortable for the passengers. Furthermore, it should be capable of accurately following high-level directions (Paden et al., 2016; Guanetti et al., 2018). The ultimate goal in decision-making is for the autonomous vehicle to move from a given point A to another point B without accidents. However, this has been an issue to achieve without the occurrence of accidents. Consequently, problem formulation related to decision-making had to be conducted to minimize the number of hazardous situations and ultimately reduce the number of accidents. (Paden et al., 2016; Guanetti et al., 2018).

Sensors play one of the most important roles in the performance of an AV. They provide data for the preceptory system to make the vehicle act or react as expected. Therefore, sensors' performance must be very accurate to avoid mistakes that would injure passengers, pedestrians, and the environment (Yan et al., 2016; Vargas et al., 2021; Yeong et al., 2021). Furthermore, the type and placement of sensors that allow an autonomous vehicle to perceive its surroundings are crucial to the performance of an AV. With these sensor placements, the vehicle is expected to provide its best performance (Vargas et al., 2021).

An AV's performance depends on several aspects embedded in the vehicle. In terms of sensor functionality issues, it poses a significant risk if there is a functional error such that the vehicle's decision is incorrect due to incorrect sensor(s) readings. Such an error could cause a fatal accident, for example, if the autonomous vehicle detects a pedestrian as not moving. While moving, the vehicle was supposed to stop at that moment but did not. Therefore, the sensors (especially the quality of data based on sensor fusion) have played a very important role in any AV performance. However, there are other very important aspects, such as the functional design structure, that analyze the collected data with the aid of sensors. Therefore, the performance of AVs proves to be a complex aspect to be measured—that is why it is crucial to measure how they are capable of obeying traffic rules.

According to Yeong et al. (2021), sensors are tools that translate environmental events or changes into quantitative measurements that can be processed further. Typically, sensors are divided into two kinds based on their core principles of operation. Firstly, the proprioceptive sensors, also known as internal state sensors, record a dynamic system's state and internal values. These sensors relate to encoders, inertia measurement units, inertial sensors (magnetometers and gyroscopes), location sensors (Global Navigation Satellite System), and receivers, such as the Global Positioning System. Secondly, the exteroceptive sensors, also known as external state sensors, sense and gather data such as distance measurements or light intensity from the system's surroundings. These sensors relate to cameras, ultrasonic sensors, Radio Detection and Ranging (RADAR), and LIDAR onboard the AV. The sensing of the environment, tracking, and localization of the AVs for trajectory planning and decision-making is a prerequisite for directing the navigation of the vehicle.

Six different driving automation levels were presented by Singh and Saini (2021). The six different levels of driving automation are grouped into two main categories: human drivers and automated driving systems. The descriptions of the different levels are further described as follows:

- *Level* 0: There is *no automation* of any sort, the driver performs all the tasks.
- *Level* 1: There are at least stand-alone vehicle components, such as automated braking; here, the *driver assists* in many operations.
- *Level* 2: There is *partial automation* such that the vehicle is capable of steering and accelerating by itself to keep the vehicle accurately in the lane(s) and adaptively moving around other vehicles. However, the human driver should always be there to monitor the operation.
- *Level* 3: There is *conditional automation* such that the human driver can take total control in certain complex situations; that is, the vehicle can drive itself in less complex situations until there is a need for human intervention.
- *Level* 4: There is *high automation* control in the vehicle, such that it can perform all needed driving functions by itself. Such vehicles might provide options for human intervention or might not provide it.
- *Level* 5: There is *full automation* such that the vehicle can perform all driving functionalities in any given situation (complex or easy) and condition.

According to Denoël (2007), the reliability index of an AV is calculated as the difference between the mean failure condition and its standard deviation. Numerous analyses used to assess and enhance the quality of goods, services, and systems are together referred to as reliability analysis. Although the term reliability can refer to a products or a system's overall performance in a generic sense, reliability is a particular measure that can be quantitatively evaluated in engineering disciplines.

According to Uzair (2021), early accidents have been recorded for AVs. There have been more than 30 accidents recorded since 2014, and about five AV passengers and pedestrians were killed by the AVs. This raised concerns among the public as an outstanding reliability challenge associated with AVs. However, these fatal accidents buttress the need for AV reliability studies for the ultimate reduction in accidents. All the decisions made by a full AV are directly based on the data gathered by the sensors and analyzed. Therefore, the sensors must function as expected to avoid obvious disasters (accidents). Now, if any of the sensors in an AV fail or provide unclean and unclear data, then that will be a big problem. Unfortunately, the sensors gather dirty data when there is a bad or abnormal weather condition (such as snow, heavy rain, etc.); this can occur in any sensor category (self-sensing, localization, and surrounding sensing). Human drivers also experience similar problems when bad or abnormal weather conditions occur (Ma et al., 2020). In their assessment (AVs) of the tenacious behavior of onboard sensors, Yan et al. (2016) examined some of the sensors by analyzing jamming and spoofing attacks in their physical channels. In the jamming attack, the sensors are made to withstand the environmental noise that occurs during typical working circumstances. In the spoofing attack, when sensors are positioned incorrectly, it is possible to get real physical signals from the incorrect source. Consequently, the discussion provided hardware and software countermeasures that may strengthen sensor resilience against attacks.

Even though AVs seek to be accident-free in their navigation ploy, this mission is still unrealistic. Hence, accountability for accidents has remained a big issue in AVs. Hence, the legal framework and regulations are integrated; this is one of the most important requirements for autonomous vehicle deployment (Singh and Saini, 2021). The main question in this situation is who should be held liable for either fatal or nonfatal accidents. This question does not have a straightforward answer; according to Borenstein et al. (2019), if there was an accident that involved AV, it does not make sense that the technology itself can be held responsible, but the designers, car dealer(s), manufacturers, and other people that could be identified as guilty. This claim supports what Mackie (2018) stated, that human drivers should remain liable for the accident depending on the automation (and the degree to which the human has control over the event(s) that led to the accident) installed in the vehicle. Suppose the automation is at level 4 or 5 (highly or fully automated). In that case, the plaintiffs are responsible for identifying who should be held accountable, which could be the manufacturers, maintainers, or others who contributed to the AV's development.

Despite having six different levels of automation for AVs according to Casado-Herráez (2020) and Singh and Saini (2021), this paper has focused on the top two levels, i.e., levels 4 and 5, of the automation hierarchical order of intelligence. Levels 4 and 5 possess the latest technological capabilities (i.e., the ability to self-drive from point A to B), including the technologies found in the lower levels (i.e., the ability to self-park). Therefore, the need to analyze the sensors that bring about the automation of the vehicles was conducted. Considering levels 4 and 5, it is crucial to look at how such systems (in terms of the functional capabilities that speak to intelligence) are designed. With a focus on how levels 4 and 5 AVs are designed, the needs analysis theory of systems engineering, was adapted to explore the conceptual design of systems with a specific focus on functional capabilities. In a nutshell, this study aims to objectively address the reliability of the intelligence of the AV with respect to traffic rules during navigation. Given the research aim, the outlined objectives include the delineation of the functional capabilities of AVs with respect to the intelligence of an AV, the modeling and analysis of the reliability of the intelligence of autonomous vehicles with respect to identified traffic rules, and the identification and analysis of the inherent complexity drivers that cause unreliability in AVs. Consequently, the reliability of the intelligence of AVs was conducted with a focus on some of the available vehicle brands in the AV industry. The analysis of these brands is provided in subsequent sections. Even though two types of K53 traffic rules were described by Hoole (2013), there are three types of traffic rules. The third rule focuses on knowing the controls of a vehicle, and an AV is assumed to know what controls it has and how to use them.

The advancement of AVs provides good news for the smart automotive industry; however, there are some potential impacts on factors such as employment, privacy, equity, etc. Considering the employment factor, the automotive industry might need more employees that understand the development of autonomous vehicles; in this case, the employment rate might increase. When considering employment related to driving, the employment rate might drop significantly. This is because most AVs are developed to provide services like that of Uber's (transporting passengers). It seems the technology will be applied to trucks as well; therefore, Uber drivers (or drivers with similar services) and truck drivers will be replaced by AVs. Though the employment predicament seems to favor the negative, there is an issue of privacy. Though services provided by companies such as Uber require passengers to have existing profiles, the AVs in addition have several cameras that will be watching the passengers, and payment may have to be always online (lack of flexibility). Some individuals might not prefer their credit or debit card details to be linked to online profiles, but that is not possible with AVs since they are void of human drivers to assist with cash transactions at the end of a trip. Nevertheless, the highlighted socio-centric factors are not considered to have any impact on the reliability of AVs based on the approach adopted in this paper for the computation of an AV's reliability. However, these factors only highlight the possibility of new policies being introduced to the social system of human endeavor to keep a good balance in the economy.

In light of the identified research gap, this paper has focused on addressing the reliability analysis of AVs by first exploring some functional attributes deemed significant for traffic rule adherence. The functional attributes or capabilities of an AV are the basis for the display of its intelligent behavior. The identification process of the functional attributes was facilitated by first creating a graphic scenario that depicts a typical outdoor road navigation situation, as presented in Figure 1 of the following section. Hence, the identification and analysis of the functional attributes of AVs were addressed prior to conducting a reliability analysis of AVs with respect to road traffic-rules. The motivation for this study is premised on the scanty literature resources in the mentioned problem domain. This study aims to objectively understudy the reliability of the intelligence of AVs amidst the inter- and intra-complexities associated with autonomous ground vehicle navigation. The associated complexities are orchestrated by the diversity of navigation requirements on the road, intelligent interactions (inter- and intra-interaction), and a need for swift decision-making.

The organization of the paper going down will first discuss and analyze the functional attributes and physical embodiment identification of AVs in Section 2. This would be followed by the reliability analysis of an AV premised on traffic rules in Section 3 while the concluding remarks and future work will be presented in Section 4.

2. Functional Attributes and Physical Embodiment Identification and Analysis

This section is focused on discussing the research approach deployed to address the identified problem. This ranges from discussions revolving around the needs and requirements as the core phase in the systems engineering conceptual design where functions originated. This continues with discussions revolving around the actual identification and enumeration of functions, the corresponding physical embodiments, and the fusion of these embodiments.

2.1 Needs and Requirement Analysis Concept

In a bid to address the reliability of AVs, the functional capabilities of AVs were first itemized and analyzed. This section presents an exploration of the systems engineering approach for functional element identification and analysis premised on the life cycle of a system. The life cycle of a system has four phases, and the first phase, which is the needs analysis phase, is concerned with the formulation of functional attributes and capabilities of a system. Kossiakoff et al. (2020) described how systems engineering theory and method can be applied to needs and requirements analysis. Needs and requirements analysis is the first phase in the origination of a new system that is either driven by technological opportunity or identified by new societal needs. This study is focused on addressing a problem driven by technological opportunities, i.e., AV born out of the emergence of Artificial Intelligence (AI). The needs and requirements analysis has two inputs, viz., operational deficiencies and technological opportunities, resulting in two corresponding outputs, viz., the system's operational effectiveness and system capabilities. One of the outputs i.e., system capabilities, was explored to provide functional capabilities for AVs in this research.

The needs and requirements analysis phase has four activities that should be considered during its execution (Kossiakoff et al., 2020); these activities are briefly discussed as follows.

- Operations Analysis: This activity is also known as "requirement analysis" in the needs analysis phase. It involves the identification of both the operational objectives and the system's capabilities.
- Functional Analysis: This activity is also known as "functional definition". Herein, the operational objectives are translated into functions, while the functions are categorized and allotted to subsystems. The results of this activity include a listing of functional requirements for the system under investigation. The functions allotted to subsystems are subsequently assigned to physical components.
- Feasibility Definition: This activity is also known as "physical definition". Herein, the physical nature of the subsystems is visualized to check if they can perform the required functions. Furthermore, a feasibility concept is defined with consideration given to the costs and capabilities of the system/subsystem/component. This activity's results are a list of initial physical embodiments that can facilitate the actualization of the identified and listed system functions.
- Needs Validation: This activity is also known as "design validation". It is concerned with the setting up of a model or some form of a validation criterion capable of checking the validity of the suggested solution(s) and the relationship between the objectives and functions, functions and sub-systems, functions and physical elements, etc.

The above-stated activity-centric steps have been utilized to create the operational objectives and system functional capabilities and identify the corresponding physical embodiments for an AV. Furthermore, two research questions were formulated herein to guide the function formation exercise and keep it within the desired scope. The questions include:

Research question 1: *What are the functional capabilities of AVs that are related to the intelligence of an AV?*
Research question 2: *What are the physical embodiments required to facilitate the actualization of these functional attributes?*
Research question 3: *What is the degree of success recorded by an AV while exhibiting driving intelligence on a busy road via its functional attributes?*

2.2 Autonomous Vehicle's Functional and Physical Requirements

Functional requirements, also known as functional capabilities, refer to attributes a system should exhibit based on the tasks or activities it is expected to perform during its operations (Kossiakoff et al., 2020). Matthaei and Maurer (2015) conducted a study to present a functional system architecture for an autonomous vehicle. The study was developed in a top-down approach based on the functional requirements of autonomous vehicles, and these requirements are described as follows:

- *Operating:* The vehicle needs instructions (these refer to the mission of the vehicle), and usually, human beings write out these instructions.
- *Mission accomplishment:* Now that the mission has been described, the vehicle should be able to accomplish the mission or the instructions, which include behavior, navigation, and control of the actuators.
- *Map data:* This data is required for route planning.
- *Localization:* The vehicle should know its location or position on a global scale for mapping data, such as navigation, and the purpose of communication in vehicle-to-vehicle or vehicle-to-infrastructure communication.
- *Environmental perception:* The vehicle should know its environment, whether it is stationary or moving, and it is expected to know the dynamic of the moveable elements.
- *Cooperation:* The vehicle is expected to respond as required in such a way that it reacts accordingly based on other traffic participants. The vehicle should also communicate its intentions to those other traffic participants.
- *Safety:* The vehicle is expected to cause no harm or danger to its environment.
- *Self-perception:* The vehicle is expected to always know its state, it should know its state in terms of its motion and functional capabilities.

In light of the above, and based on the principles of architecture premised in the "structure of systems" as depicted herein, ***{{System=>Sub-system(1),Sub-system(2),….,Sub-system(n-1), Sub-system(n) => Component(1), Component(2),….,Component(n-1), Component(n)=>Sub-component(1), Sub-component(2),…..Sub-component(n-1),Sub-component(n)=> Part(1), Part(2),….Part(n-1),Part(n)}}*** as anchored in the systems engineering approach, the physical embodiment responsible for the actualization of the functions would form the next item of discussion. The physical embodiments with functional capability are often seated at the component and/or sub-component levels, while the functions are seated at the sub-systemic level.

Furthermore, it should be noted that the hardware or physical embodiments responsible for the display of intelligence in AVs are mostly "sensors" with diverse sensing capabilities. These often vary from proximity to ranging sensors. Some commonly used sensors on AVs include the LIDAR sensor, RADAR sensor, camera or vision sensor, and ultrasonic sensors. The need to integrate two or more of these sensing devices, also known as sensor fusion, will be discussed subsequently. The *system capabilities* (the capacity of a system to carry out a specific action or produce a desired result under a specific set of circumstances or conditions) of an AV refer to the functional capabilities. These capabilities are identified when systems engineering theory is applied. The identified functional capabilities are presented below. Functions are often represented using action phrases.

(i) *Ability to combine a range of sensors*, including the Global Positioning System (GPS), Odometer, Radar, LIDAR, Sound Navigation Ranging (SONAR), thermographic cameras, and inertial measurement units, to sense their environment. This functional capability is aimed at effectively gathering data.

(ii) *Ability to control systems and analyze sensory data* to determine the best routes to take, as well as barriers and essential signage, in a more advanced manner.

(iii) *Ability to detect* lanes using a camera system to read the markings on the road and keep the vehicle within its right (or safe) lane.

(iv) *Ability to make safe decisions* based on how other vehicles surrounding the AV are behaving using a *vehicle-to-vehicle communication technique*. Whereby the AV must be aware of the position, velocity, and trajectory of any close vehicles.

(v) *Ability to use a decision-making system* built into it (the AV) to make informed decisions, such as reacting when other vehicles behave abnormally, to prevent accidents.

To provide more perspective on the circumstances or conditions AVs are expected to adhere to or would likely be exposed to while on the road, two scenarios were created using Any Logic software, as shown in Figure 1. These representative road scenarios present a mixed driving scenario from other road users, covering good and bad road usage.

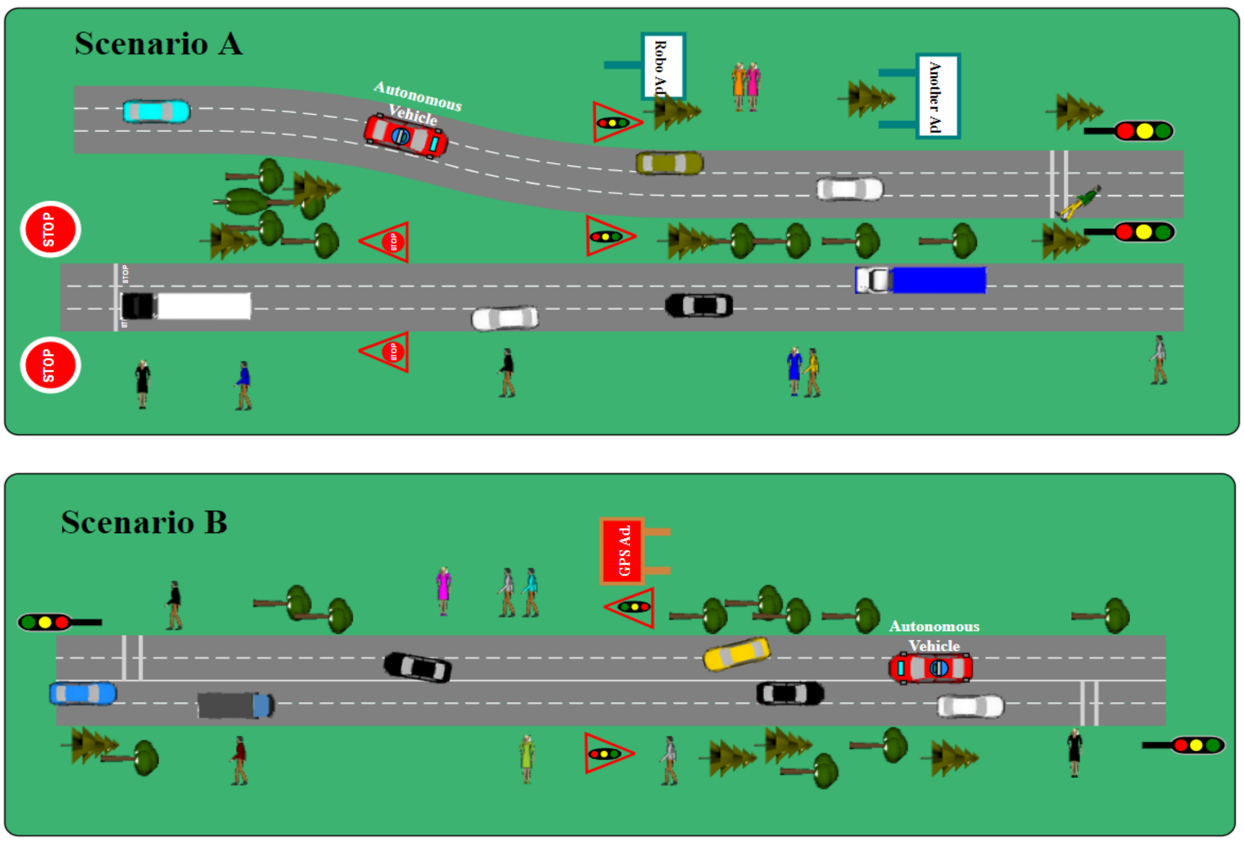

Figure 1. Two scenarios depicting general road signs, signals, and hazards AVs would interact with on the road.

Considering Figure 1, scenario A represents a dual carriageway whereby vehicles on a particular road carriage only move in one direction. For example, the vehicles on the bottom road (in Scenario A) are expected to navigate from the right end of the sketch to the left, and the vehicles on the top road are expected to only navigate from the left end of the sketch towards the right direction. Furthermore, scenario B represents a single carriageway. A single carriageway is a road facility with one, two, or more lanes set up within a single road facility without any central reservation to divide traffic flow in the opposite direction except the road line marks.

In scenario A, the AV is expected to stay in its lane before notifying other road users that it intends to change lanes; hence, doing that intelligently is a requirement to avoid accidents. Furthermore, the AV should be able to read the traffic light warning signs, drive at a speed limit, not misread the pedestrian zebra crossing line, billboards, or even roadside trees for something they are not, and also obey the traffic light rules as prompted. In this scenario, the AV does not have to worry about other vehicles that move in the opposite direction. Regarding Scenario B, the situation could get trickier as the AV is expected to watch out for vehicles that move in the opposite direction. If, for example, the black vehicle close to the AV (the AV in red) decides to turn left for some odd reason, the AV is expected to react accordingly. However, the AV in Scenario B should never cross the white solid line unless it has lost control. In essence, AVs are expected to obey traffic rules; hence, 30 traffic rules were extracted from the created scenario in Figure 1 in conjunction with the information obtained (Hoole, 2013). There are two types of traffic rules. Firstly, there are the *road signs, signals, and markings* (Table 1), and secondly, there are the *rules of the road* (Table 2).

Table 1. Road signs, signals, and markings rules utilized to assess the reliability of AVs.

Road signs, signals, and markings—The purpose is to safely regulate traffic flow, warn drivers or motorists of the circumstances on the road ahead, provide the useful and necessary information, and provide guidance on routes and destinations.	
Rule 1	Regulatory signs—*must obey*.
Rule 2	Traffic signals—*must obey*.
Rule 3	Warning signs—*must heed to avoid potential danger*.
Rule 4	Hazard marker plates—*must heed to avoid potential danger*.
Rule 5	Information signs—*must understand to react appropriately*.
Rule 6	Guidance signs—*must be built in the AV*, for instance, using a Global Positioning System (GPS).
Rule 7	Tourism signs—*not important* simply because AVs must have built-in GPS which they can use to navigate to a desired tourist's destination.
Rule 8	Diagrammatic signs—*must heed to select an appropriate lane*.
Rule 9	Road surface markings—*must obey*.
Rule 10	Hand signals—*must obey* if it is a traffic officer and *must heed* if it is other motorists.

Table 2. Rules of the road utilized to assess the reliability of AVs.

Rules of the road—The purpose of the rules of the road is to *control traffic*, *provide safety*, and *safeguard everyone's right to use the road*. Speed restrictions, lane discipline, parking, and lighting all have regulations that must be adhered to. The following traffic rules are required and doing so will significantly lower the likelihood of roadway accidents, injuries, and fatalities.	
Rule 1	The vehicle must drive on the correct side (left or right) of a two-way road.
Rule 2	The vehicle must travel on the right or left side of a one-way road if it is safe.
Rule 3	The vehicle must obey a traffic officer's instructions over the rules of the road and road signs.
Rule 4	The vehicle must keep a following distance that is appropriate and prudent, considering the speed of the vehicle being followed, the amount of traffic, and the state of the road.
Rule 5	Speed limit (in km per hour) of 60, 100, and 120 for when the vehicle is in an urban area, outside an urban area, and on a freeway, respectively.
Rule 6	The vehicle should not cross over the solid driving marking (yellow or white).
Rule 7	The vehicle should drive over to the left lane and not accelerate when overtaken.
Rule 8	The vehicle should always signal its intentions in time before it executes it, and it should execute only when it is safe to do so.
Rule 9	The vehicle should not stop on the road unless an accident had to be avoided, a traffic officer or road sign(s) had instructed, or it was caused by an unavoidable cause (such as mechanical problems).
Rule 10	At a roundabout or mini circle, the vehicle must give way to other vehicles that approach from the right (the other vehicle(s) should be already approaching from the right or stopped on the yield sign first). The vehicle should also know when to yield at other intersections (such as four-way, three-way, etc.).
Rule 11	The vehicle may not enter a traffic lane or cross it if it is likely to cause a dangerous situation or disrupt traffic flow.
Rule 12	The vehicle should not turn if it will obstruct or cause danger to other traffic. Therefore, before turning, the vehicle must move to the right lane, indicating its necessary intentions, and turn when it is safe to do so.
Rule 13	The vehicle should never park on the sidewalk or the verge. Therefore, it should park within a designated parking space.
Rule 14	The vehicle should always give way to the emergency vehicles, rescue vehicles, traffic officer's vehicles, etc. when they signal with the siren.

Table 2 continued…

Rule 15	The vehicle must stop for pedestrians on, or about to enter, a pedestrian crossing on its side of the road or if it is involved in an accident.
Rule 16	The vehicle must use hookers for safety reasons only, and the hooter must be audible enough for a distance of at least 90 meters. Furthermore, the tone of the pitch should not vary for any reason.
Rule 17	The vehicle must have white headlights, they should be switched on between sunset and sunrise, and they should be switched on if visibility is not clear at greater or equal to 150 meters.
Rule 18	The vehicle may not drive in a way that endangers the lives of other drivers or pedestrians (the vehicle will always be liable if it hits a pedestrian regardless of who had the right to the way in the road) or damage any property.
Rule 19	The vehicle should ensure that the passenger(s) fasten the seatbelts before they start moving.
Rule 20	The vehicle should stop immediately after an accident. If someone dies or gets injured, the vehicle should not move without a traffic officer's authorization.

Given the scenarios in Figure 1, and the traffic rules created in Table 1 and Table 2, the functional elements of AVs, their corresponding physical embodiments, and the targeted traffic rules were identified and matched as shown in Table 3. As earlier mentioned, functions are capabilities that AVs must possess to facilitate their intelligent adherence to road traffic rules.

Table 3. The functional elements of AVs matched with their physical embodiments and traffic rules.

Functional elements	**Physical embodiments**	**Targeted traffic rules**
Visualization of road signs.	Camera sensor.	Table 1: Rule 1, Rule 3, Rule 4, Rule 5, and Rule 8.
Object detection, such as other vehicles, pedestrians, etc.	LIDAR, RADAR, and Camera sensors.	Table 2: Rule 15
Visualization of hand signals by an officer.	Camera sensor.	Table 1: Rule 10, Table 2: Rule 3
Visualization of road surface markings.	Camera sensor.	Table 1: Rule 9, Rule 6, Table 2: Rule 7, Rule 11
Visualization of objects in 360 degrees.	LIDAR sensor.	Table 2: Rule 18
Speed detection of other vehicles.	RADAR and Camera sensors.	Table 2: Rule 4, Rule 11
Distance detection between AV and other vehicles (s).	RADAR, LIDAR, and Camera sensors.	Table 2: Rule 11
Distance detection between the AV and pedestrian(s).	RADAR, LIDAR, and Camera sensors.	Table 2: Rule 15
Lane detection.	Camera sensor.	Table 2: Rule 1, Rule 2,
Emergency stop due to dangerous or potentially dangerous situations.	Ultrasonic sensor.	Table 2: Rule 15 and Rule 20
Interpretation of road signs, signals, and markings.	Camera sensor.	Table 1: All rules.
Object Classification.	Camera and LIDAR sensors.	Table 2: Rule 11, Rule 14

2.3 Sensor Fusion Analysis

With the functional requirements outlined, the physical requirements of AVs can also be provided, which is a feasible functional structure. However, the sensor fusion analysis had to be conducted first to re-design a feasible structure. When considering the nature of the AVs, more specifically what makes them autonomous, the primary aspect is the components that gather data, i.e., the sensors. Consequently, the analysis of sensors was utilized to reconfigure the raw data layer. The sensors of the vehicles are chosen in such a way that optimal performance is achieved. Therefore, sensors that were specified by Yeong et al. (2021) and Ignatious and Khan (2022) were used to select the best three for camera and LIDAR, and the best two for RADAR (Tables 4, 5, and 6).

Table 4. The top three best-performing LIDAR sensors in terms of vertical Field-of-View (FOV), horizontal FOV, and range.

LIDAR sensor	**Vertical FOV (◦)**	**Horizontal FOV (◦)**	**Range (m)**
Velodyne Alpha Prime	40	360	245
Velodyne VLP-32C	40	360	200
Velodyne RoboSense	40	360	200

Table 5. The top three best-performing camera sensors in terms of lens baseline–it provides optimal view range, range, and lens resolution.

Camera sensor	Baseline (mm)	Range (m)	Resolution (MP)
Intel D15	55	10	3
RealSense D435	50	10	3
Framos D435e	55	0.2–10	2

Table 6. The top two best-performing RADAR sensors in terms of overall frequency.

RADAR sensor	Overall frequency Giga-Hertz (GHz))
Smartmicro UMRR-96 T-153	79 (usually in 77 to 81)
Continental ARS 408-21	76 to 77

Additionally, the fusion of sensors was analyzed to identify the best fusion option for the LIDAR, camera, and RADAR sensors. Vargas et al. (2021) and Yeong et al. (2021) have already provided an analysis of these sensors. However, this study analyzed the fusion of lesser sensors (fusion of only two sensors). This was necessary since these sensors are expensive (especially the LIDAR). According to the Neuvition website, Velodyne 64-line LIDAR is $80,000 (≈R1.5 million). The Smart micro RADAR sensor is £2,725.00 to £2,995.00 (≈ R55,712.92 to R61,233.10) according to the Level Five Suppliers website. The Continental ARS 408 is between R729.06 and R13,155.87 according to the AliExpress website. Finally, the Intel D415 costs $317.95 (≈ R5,750.39), RealSense D435 costs $317.50 (≈ R5,742.25), and the Framos D435e costs €945.10 (≈ R16,861.39) according to Spark fun, B & H Photo Video Audio Mouser Electronics websites.

Table 7. The comparison of AV sensor fusion based on the comparison provided by Yeong et al. (2021).

Factors	Camera	LIDAR	RADAR	2-Fusion	3-Fusion
Range	0.5	0.5	1	1.5	2
Resolution	1	0.5	0	1	1.5
Distance Accuracy	0.5	1	1	1.5	2.5
Velocity	0.5	0	1	1.5	1.5
Color Perception (traffic lights etc.)	1	0	0	1	1
Object Detection	0.5	1	1	1.5	1.5
Object Classification	1	0.5	0	1	1.5
Lane Detection	1	0	0	1	1
Object Edge Detection	1	1	0	1	2
Illumination Conditions	0	1	1	1	2
Weather Conditions	0	0.5	1	1	1.5
Total				13	19
Good Fusion (greater than 11?)				Yes	Yes

Therefore, the analysis of two sensor fusions (camera and RADAR) and three sensor fusions (camera, LIDAR, and RADAR) was conducted, as seen in Tables 7 and 8. The goal was to check if the two-sensor fusion would meet the minimum requirement of fusing all factors or features of each sensor so that they produce optimal results. Furthermore, the comparison rates (0, 0.5, 1) in Table 7 were described as follows.

0: The sensor does not operate well in respect of the specified functional attribute.
0.5: Sensor performs reasonably well in respect of the specified functional attribute.
1: Sensor operates perfectly well in respect of the mentioned functional attribute.

It can be noted that the last row in Table 7 assesses whether the fusion of two or three sensors is good or not. A criterion of ≥11 was used on the ground that 11 factors were assessed *and* all values in blocks

representing *2-Fusion* and *3-Fusion* are ≥1. Furthermore, to further analyze the comparison seen in Table 8, the comparison rates (0, 0.5, 1) are described as follows,
Poor, Yes: 0
Average: 0.25
Good, 200m: 0.5
Very good, No, 250m: 1.

Table 8. The comparison of AV sensor fusion based on the comparison provided by Yeong et al. (2021).

Factors	Camera	LIDAR	RADAR	2-Fusion	3-Fusion
Range	0.5	0.5	1	1.5	2
Resolution	1	0.5	0.25	1.25	1.75
Affected by weather conditions	0	0	0	0	0
Affected by lighting conditions	0	1	1	1	2
Detects speed	0	0.5	1	1	1.5
Detects distance	0	0.5	1	1	1.5
Interference susceptibility	1	0.5	0	1	1.5
Total				**6.75**	**10.25**
Good Fusion (6)				**Yes**	**Yes**

The criteria used in the last row of Table 8 are the same as those used in Table 7. However, a value of ≥ 6 was used instead of ≥ 7 since there are seven rows because the third factor tested consisted of zeros. Therefore, both sensor fusions will always result in a zero (sensor fusion is always poor). With the sensors analyzed, a feasible functional design structure is in place.

3. Reliability Analysis of AVs and Traffic Rules (Contribution)

This section presents the reliability analysis of the functional embodiments associated with the exhibition of intelligent functional capabilities in AVs. The embodiments considered in this paper are predominantly sensor-based. The reliability analysis and assessment were with respect to AVs obeying traffic rules and road signs while in transit.

3.1 Data Gathering and Reliability Analysis

The performance assessment herein focuses on the operational objectives. Therefore, if the AVs obey traffic rules, that means the vehicle can meet the operational objectives discussed in the operational objectives phase. For example, suppose an AV can transport a passenger from point A to B without any harm to anyone or anything (successfully protecting both its passenger(s) and its external environment) and does that *consistently*, it can be deduced that it obeyed all the traffic rules. These kinds of measures will allow AVs to be commercialized in cities so that they provide the required services. Further, this provides the opportunity for cities to have more advanced vehicles and move closer to a *smart city era*, depending on the technological state of that city.

The videos in Table 9 were selected from top AV companies, while the traffic rules earlier provided in Tables 1 and 2 were analyzed with respect to the videos to create Tables 10 and 11 for the assessment of the reliability of the AVs. Furthermore, these rules can also be used for AVs that are not yet manufactured (i.e., assessment based on these rules can be deployed via simulation on an ongoing AV design process or experimental prototypes). With these rules in place, the analysis indicates which rule(s) were passed, failed, or not tested during the validation process of the AVs. The AV results presented and analyzed here came from different companies that made their vehicles available for public testing. The tests were recorded and made available online in video clips. The links to the videos are provided in Table 9. The video links can be opened with a simple click.

Table 9. Video links related to AVs of different companies.

Vehicle brand	Video link
Tesla models	Video Test 1 Video Test 2 Video Test 3 Video Test 4 Video Test 5 Video Test 6 Video Test 7
Deeproute	Video Test 1
Cruise	Video Test 1
Waymo	Video Test 1 Video Test 2 Video Test 3 Video Test 4
AutoX	Video Test 1 Video Test 2 Video Test 3 Video Test 4
Pony AI	Video Test 1 Video Test 2 Video Test 3 Video Test 4
Yandex	Video Test 1 Video Test 2 Video Test 3

3.1.1 Reliability Analysis

The purpose of this section is to provide the *reliability of AV with respect to obeying traffic rules* by conducting a reliability analysis using *reliability engineering* and *statistics* theories. Therefore, the rules outlined in Tables 1 and 2 were used to assess the AVs seen in the videos that are provided in Table 9 to first obtain the time-to-failure data prior to addressing the AV's reliability. It was necessary to record time stamps at which the AVs failed to adhere to the traffic rules to apply the statistical analysis to the time data. The first step was to assess which rule was obeyed, disobeyed, or not tested and taking into consideration which AV company the test relates to. Furthermore, five AV companies were identified (which are Tesla, AutoX, Waymo, Deeproute, Yandex, Pony AI, and Cruise) and analyzed, and the outcomes can be seen in Tables 10 and 11.

Table 10. The reliability analysis of AV with respect to traffic rules—part A (road signs, signals, and markings rules).

Vehicle brand	Road signs, signals, and markings traffic rule						
	Tesla Model 3	**AutoX (robotaxi)**	**Waymo (by Google)**	**Deeproute**	**Yandex**	**Pony AI**	**Cruise**
Rule 1	1	1	1	1	1	1	1
Rule 2	1	1	1	1	1	1	1
Rule 3	0	0	0	0	0	0	0
Rule 4	0	0	0	0	0	0	0
Rule 5	1	1	1	1	1	1	1
Rule 6	1	1	1	1	1	1	1
Rule 7	0	0	0	0	0	0	0
Rule 8	0	1	1	1	1	1	1
Rule 9	0	1	1	1	1	1	1
Rule 10	0	0	0	0	0	0	0
Passed	**4**	**6**	**6**	**6**	**5**	**6**	**6**

Table 10 represents an analysis outcome of the AVs' performance of all five AV companies with respect to the road signs, signals, and marking rule type. Table 11 represents an analysis outcome of the AVs' performance of all five AV companies with respect to the rules of the road rule type. The descriptions of the (red "zeros", black "zeros" and green "ones") in Tables 10 and 11 are described as follows.

1: Rule tested and *passed*.
0: Rule tested and *failed*.
0: Rule *not tested*.

Table 11. The reliability analysis of AV with respect to traffic rules—part B (rules of the road).

Vehicle brand	**Rules of the road**						
	Tesla Model 3	**AutoX (robotaxi)**	**Waymo (By Google)**	**Deeproute**	**Yandex**	**Pony AI**	**Cruise**
Rule 1	1	1	1	1	1	1	1
Rule 2	1	1	1	1	1	1	1
Rule 3	0	0	0	0	0	0	0
Rule 4	1	1	1	0	1	1	1
Rule 5	0	1	1	0	0	0	0
Rule 6	0	1	1	1	0	1	1
Rule 7	0	0	0	1	0	1	1
Rule 8	1	1	1	0	1	1	1
Rule 9	0	1	1	1	0	1	1
Rule 10	0	1	1	1	0	1	1
Rule 11	0	1	1	1	1	1	1
Rule 12	0	1	1	1	1	1	1
Rule 13	1	0	0	0	0	0	0
Rule 14	0	0	1	0	0	0	0
Rule 15	0	1	0	1	0	1	1
Rule 16	0	0	0	0	0	0	0
Rule 17	0	0	0	0	0	0	0
Rule 18	0	1	0	1	0	1	1
Rule 19	1	0	0	0	0	0	0
Rule 20	0	0	0	0	0	0	0
Passed	**6**	**12**	**11**	**10**	**6**	**12**	**12**

Table 12. Total passed traffic rules by different autonomous vehicle (AV).

Vehicle brand	Tesla Model 3	AutoX (robotaxi)	Waymo (By Google)	Deeproute	Yandex	Pony AI	Cruise
Total passed	10	18	17	16	11	18	18
%	0.3333	0.6000	0.5667	0.5333	0.3667	0.6000	0.6000

As observed in Table 12, AutoX (robotaxi), Pony AI, and Cruise have the same traffic rule pass, and they are the highest, i.e., they are the top three AV companies that are currently doing well. The Tesla Model 3 was found to be the least-performing AV. Therefore, Tesla was eliminated in further reliability analysis as it was concluded to have an autonomous level of less than four. The Tesla AVs tested did not make use of LIDAR sensors, which provide a 360-degree view. That could be one of the factors that contributed to its poor performance. Additionally, the time stamps were recorded every time the vehicle disobeyed any traffic rules as earlier outlined in Tables 10 and 11. The time-to-failure dataset gathered is presented in Table 13. As shown, Table 13 provides the sample size (n=33) of the time-to-failure, as one AV could fail at least one traffic rule more than once. To gather the time-to-failure in Table 13, the following assumptions were made.

- The maximum timestamp considered from the videos was 20 minutes, and there was no minimum timestamp considered. This assumption was created so that there is a limitation as to how long each test was conducted so that a hypothesis test can be formulated. Though no hypothesis test was formulated, it should be noted that the reliability analysis focused on disproving if the AVs would fail at least one of the traffic rules in 20 minutes.

- The AV companies are disregarded, i.e., all AV companies' vehicles are regarded as different AVs tested. This assumption was created since the reliability of AVs (not AV companies) was to be addressed.
- All AVs tested have all the important sensors onboard, i.e., LIDAR, RADAR, cameras, and ultrasonic sensors.

Table 13. Time-to-failure of AVs observed in the analyzed videos.

Number of observations (n)	**Time-to-failure (*ti*, in minutes)**
1	0.19
2	0.32
3	0.32
4	0.40
5	1.04
6	1.14
7	1.50
8	1.54
9	2.08
10	2.10
11	2.13
12	2.15
13	2.21
14	2.29
15	2.46
16	2.52
17	2.56
18	2.59
19	3.14
20	3.37
21	3.47
22	4.41
23	5.03
24	5.29
25	5.47
26	5.57
27	6.24
28	6.55
29	7.22
30	7.39
31	11.04
32	13.37
33	17.07

It is important to note that some of the individuals that provided the videos were biased towards their products (making it seem as if they did not make mistakes), such as the Deeproute company. However, the kind of bias found in the videos focused on how well the AVs were trying to make successful decisions rather than obeying traffic rules. Hence, assessing if the AVs obey traffic rules is a better way to assess the reliability of an AV. This assessment reflects the AVs' overall performance and safety in the cities. However, since there were biases noted in the testing of other AVs, the reliability calculated later in the paper is not a 100% reflection of the AVs' performance, but it is close enough as some of the biases were countered by the nature of the assessment conducted on the videos.

Prior to conducting the reliability analysis, a couple of mathematical symbols and notations would be introduced, as presented in Table 14. While some of these symbols are variables, others are parameters. However, each of these symbols would be described as they are utilized in the modeling process.

Table 14. Definitions of mathematical symbols for reliability analysis.

Symbol	Definition
τ	t-zero, which represents the location parameter, describes the shifting of the scale parameter from the origin.
β	Beta, which represents the shape of a graph.
α	Alpha measures the reliability of the scale such that it communicates how strong is the internal consistency, i.e., it tells how consistently items were measured.
η	Eta, which represents the scale parameter of the Weibull, describes how the time (t) parameter ages.
λ	Lambda, which is calculated as 1/mean.
ln	Natural logarithm.
n	Sample number (or number of observations).
t	Time at which an item (AV) failed to adhere to traffic rule(s).
i	Order number of failed items.

To conduct the reliability analysis of the AVs, the distribution of the time-to-failure dataset had to be evaluated so that a reliability analysis technique could be selected. The distribution of the time-to-failure dataset was found to follow a Weibull distribution with shape parameter $\beta < 1$, with a *mean value of* 4.066 minutes (Figure 2).

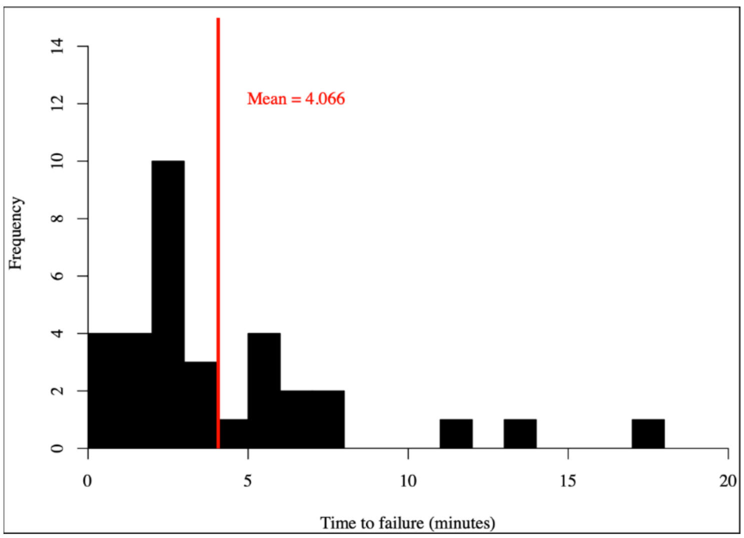

Figure 2. Time-to-failure distribution.

The Weibull distribution is widely used in the reliability analysis of a wide variety of systems due to its shape-adaptable ability. This shape-changing ability of the Weibull distribution such that it takes the form of another distribution type is referred to as a special case. The Weibull distribution has been found to appear in five different forms, with the three-parameter and two-parameter being the two common forms (Hallinan Jr, 1993; Lai et al., 2006). The three-parameter has the τ, β, and α (or η) parameters. When the $\tau = 0$, the Weibull distribution is two-parameter based. The three-parameter Weibull distribution was chosen for this study since the parameter τ was useful as the vehicle cannot fail one of the traffic rules at zero minutes.

- The reliability model was created using a probability plotting approach premised on parameter estimation. The following are three simple ideas involved in conducting this method.
- A visual representation of the data is produced on a specialized probability plotting paper (different for each statistical distribution).
- Utilize a probability plotting paper with transformed axes to ensure that a genuine Cumulative Density Function (CDF) plots as a straight line (linearization).

- The data is deemed to suit the appropriate distribution if a straight line can fit the plotted data —this can be interpreted as an assumption.

To implement the method, the time-to-failure dataset should be linearized by calculating the *median rank* of the data. The median rank is the cumulative percentage of a population in a given data sample with a 50% confidence level. To calculate the median rank, Bernard's approximation was utilized, and the ranks are calculated using Equation (1) (Lai et al., 2006; Firdos et al., 2020),

$$Median\ rank\ (r_{ti}) = 100\left(\frac{i_{ti}-0.3}{n+0.4}\right) \tag{1}$$

where,

$$i_{ti} = i_{ti} + N_{ti} \tag{2}$$

$$N_{ti} = \frac{(n+1)-i_{ti}}{1+(n-number\ of\ preceding\ items)} \tag{3}$$

i = order number of failed items, $0 > i \le n$, and n = sample size.

It should be noted that $i = ti$ when conducting the calculations. The values produced by r_{ti} (see Equation 1) are in %, which are further used to calculate the y-axis of the Weibull probability plot. The unreliability Equation of the three-parameter Weibull distribution is provided in Equation (4). This Equation was linearized to produce Equation (5) by applying a double natural logarithm.

$$F(t) = 1 - e^{-\lambda(t-\tau)^{\beta}}, t > \tau \tag{4}$$

$$y = \beta ln(\lambda) + \beta ln(t-\tau) \tag{5}$$

where,

$$\lambda = \frac{1}{mean} \tag{6}$$

The value of τ is the value that cuts the x-axis after plotting the calculated linearized values. The value of η is the x-axis value that cuts through the plotted graph when plotted with the value ln (−ln(1 − 0.6320)). The value of τ can be seen as t_0. The value of β is the slope of the fitted straight line. The value of λ in a Weibull distribution is interpreted as the failure rate and calculated as seen in Equation (6). Since the λ value is also important to evaluate the reliability of the AV, and the dataset is not large, a bootstrap method was adopted to recalculate the λ value. A bootstrapping method is one that generates a large number of phantom samples known as bootstrap samples by re-sampling (with replacement) from the sample data at hand. The sample summaries for each bootstrap sample are then calculated (usually a few thousand or thousands). The main idea of using the bootstrapping method is to conduct the same experiment without expanding additional time and resources. Bootstrapping was carried out to calculate a mean value that would satisfy the time-to-failure data set which would have been observed at least 10,000 times (similar to conducting a simulation run), i.e., resampling from the originally observed data set about 10,000 times. The resampling should have the same number of observations (n) and duplication is allowed, for example, if the original data set has n=30, then the first randomly resampled data set should have n=30. Furthermore, with the resampled data sets, anything can be calculated or addressed. In this study the mean value is the target.

The time-to-failure data set and the Weibull plot were analyzed and plotted in RStudio software using the R programming language. The median ranks and confidence interval calculations were conducted in Anaconda software using the Python programming language. In consideration of the analysis of the linearized Weibull distribution, the RStudio software was utilized to conduct the plotting by making use of the wblr() and wblr.fit() functions, which required an R-Package called WeibullR (see the graph in Figure 3). Figure 3 shows a linearized Weibull plot using a special sheet of the time-to-failure data set. It is important to note that the section with the title censored dataset provides the most important details of the graph. The three parameters of the Weibull distribution are extracted from Figure 3 (see Table 15).

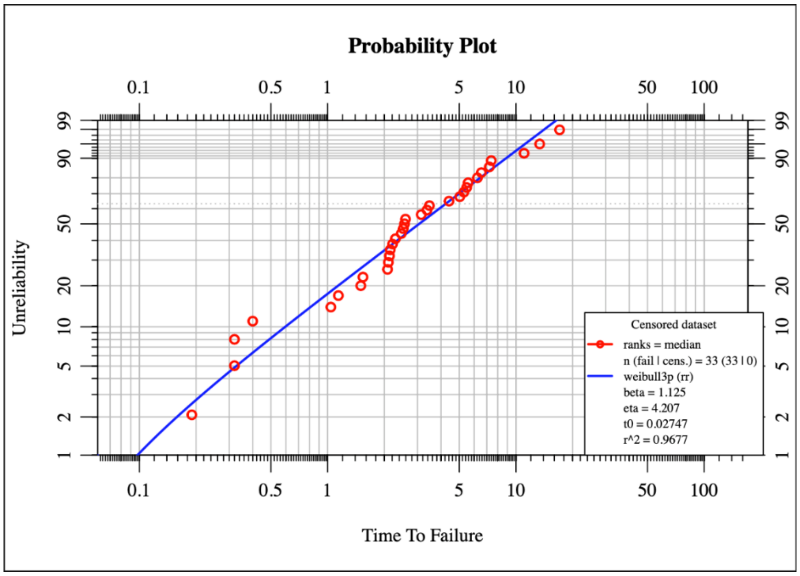

Figure 3. The linearised fitted Weibull distribution plot.

Table 15. The three-parameter Weibull distribution from the time-to-failure data.

Parameter	Value (minutes)
Shape (β)	1.1550
Scale (η)	4.2400
Location (t0 = τ)	0.9675

Given three parameters as shown in Table 15, one more parameter is required to calculate the reliability, and this parameter happens to be the mean. To calculate the mean, a bootstrap method had to be applied to accurately determine the mean that best describes the time-to-failure data set. Based on this, the bootstrap was performed using the boot() function in RStudio, premised on the R programming language. The boot() function, in this case, requires three arguments namely: the time-to-failure data set, the sampling function (of which the R sample() function was utilized), and the number of replications or resampling, which is 10,000 in this research. The distribution of the bootstrapped values of time-to-failure was plotted and matched with the one in Figure 2. The new mean value ($mean_{new}$) from the bootstrap was calculated to be 4.058 minutes, and the 95% confidence interval of the mean is ∈ [2.87, 5.45]. This signifies that a mean value of 4.058 minutes can be utilized since it is within the 95% confidence interval. In this study, $mean_{new}$ = 4.058 minutes was utilized since it was calculated using a bootstrap approach, hence, λ = 1/4.058 resulted in a magnitude of 0.2464 per minute. Values calculated from a bootstrap approach are closer to the actual values, hence their adoption. With all these parameters in place, both Equations (4) and (5) are fully sorted, as seen in Equations (7) and (8),

$$F(t) = 1 - e^{-0.2464(t-0.9675)^{1.155}} \tag{7}$$

$$y = 1.155ln(0.2464) + 1.155ln(t - 0.9675) \tag{8}$$

Let $x = ln(t - \tau)$, Equation (9) can be rewritten as follows,

$$y = 1.155ln(0.2464) + 1.155x.$$

therefore,

$$y = 1.155x - 1.6179 \tag{9}$$

To answer the question "What is the reliability of an AV in respect of traffic-rules?" Equation (7) is expected to provide the solution. The assumption that AVs are tested for 20 minutes was utilized to define a finite time frame to test the AVs. Therefore, the reliability of an AV at 20 minutes is calculated as follows,

$$\begin{aligned} R(t) &= 1 - \left(1 - e^{-0.2464(20.00-0.9675)^{1.155}}\right), \\ &= e^{-0.2464(20.00-0.9675)^{1.155}}, \\ &= 6.089 \times 10^{-4}, \\ &= 0.06089\ \%\ \text{reliable.} \end{aligned}$$

Consequently, there is a $1 - R(t) = 99.94\%$ chance that an AV will fail at least one of the traffic rules in 20 minutes. This is because of the increasing hazard rate $h(t)$. The hazard rate increases when $\beta > 1$. In this case, $\beta = 1.155$ which implies a high hazard rate. Hence, the goal is to decrease the hazard rate, i.e., make ($\beta \leq 1$).

4. Conclusion

This research will form a useful rallying point for all AV manufacturing industries, especially those whose AV performance was analyzed herein, including captains of industries, researchers in the field of smart systems, and policymakers on autonomous systems, amongst others. The research has focused on providing more insight into the reliability of AVs. The reliability assessment measures addressed in this paper focused on adherence to traffic rules. Traffic rules have been established to protect the environment, pedestrians, and drivers or passengers in other vehicles. Therefore, if the AVs can adhere to traffic rules, they will be seen as reliable. Even though the sub-systems that make up an AV system are not operationally perfect, just like the humans who designed and manufactured them, the reliability of an AV is strongly linked to the functional and operational success of its member elements. The reliability analysis of AVs is a challenging task, and following that, all traffic rules must be obeyed and passed. If an AV adheres to a traffic rule with a success rate of less than 100%, that AV is considered to have failed such a rule. Hence, finding common and consistent ground in computing a feasible reliability measurement for an AV is crucial.

In this research, some core functional capabilities of an AV were first identified and outlined by following the systems engineering conceptual design principle. These were in turn linked to the created and adapted traffic rules for further analysis, leading to the reliability analysis. Considering the findings herein, the literature has pointed out that functional requirement identification is a core requirement when designing an AV. Following that, there is a clear integration between functional requirements, the corresponding physical elements, and the expected performance of an AV. It is significant to proceed in this sequence when designing systems in general. When considering the design of an AV, the activities can vary among different design processes with sensor fusion creating an important variant. This research addressed the problem of sensor mix, through different kinds of sensor combinations. It is important to identify and select sensor types that yield the best performance for more efficient data gathering. As a way of addressing future work, the identified capabilities would require some real-life AV validation since there are no confirmed data available in the literature to do this.

Furthermore, considering the reliability analysis conducted in this research, the time-to-failure data set was gathered and analyzed to aid in the identification of a reliability analysis method, which in this paper, resulted in the linearized Weibull plotting method. The time-to-failure results were validated through bootstrapping, and the lambda parameter was extracted from the bootstrap results for more accuracy. The method was applied mostly by using the R and Python programming languages. The results showed that there is a 99.94% chance that an AV will fail at least one of the traffic rules. Furthermore, the hazard rate was found to be increasing. Considering these findings, it can be deduced that the AVs can still not be fully commercialized, but they are very close to getting there. One major issue of concern is that AVs have demonstrated a high level of uncertainty when it comes to multi-tasking with decision-making on the road in a bid to avert accidents.

For future work in a bid to extend this research, the following would be considered: Firstly, data gathering would be improved. One way to do this is to access real AVs from different AV companies and test them while recording the data. Also, several AVs from the same company would be assessed for more accuracy and consistency. Even though this will be a lengthy task, it is considered significant for more effective reliability analysis. Secondly, recalculating the reliability using different alternate methods apart from the linearized Weibull plotting method premised on probability plotting can be an additional step in the right direction. Finally, the need to reduce the hazard rate of AVs through the improvement of their reliability is quite significant. To improve the reliability of AVs', it is recommended that the developers and manufacturers consider developing their AVs to meet the traffic rules' requirements. One key feature that was seen to be absent from the sampled AVs is the inability to warn pedestrians or human drivers using the hooter, which is meant to be a requirement for safety. Meeting these requirements will surely be challenging, as the overall performance of the AVs does depend on the integration of systems that have their own individual, different, and specific tasks to be executed, even though they remain linked as a whole system. Therefore, the decision-making system of AVs needs to be improved. It is strongly recommended that AVs be developed to perform satisfactorily in level 4 of automation, i.e., validated via testing and computation of their reliabilities with respect to traffic rules and deemed satisfactory prior to moving to the next level of automation, level 5.

Conflict of Interest
The authors of this research wish to state that there is no any conflict of interest regarding this research.

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References

Badue, C., Guidolini, R., Carneiro, R.V., Azevedo, P., Cardoso, V.B., Forechi, A., Jesus, L., Berriel, R., Paixão, T. M., Mutz, F., de Paula Veronese, L., Oliveira-Santos, T., & De Souza, A.F. (2021). Self-driving cars: A survey. *Expert Systems with Applications*, *165*, 113816. https://doi.org/10.1016/j.eswa.2020.113816.

Borenstein, J., Herkert, J.R., & Miller, K.W. (2019). Self-driving cars and engineering ethics: The need for a system level analysis. *Science and Engineering Ethics*, *25*(2), 383-398.

Casado-Herráez, D. (2020). *Self-driving car autonomous system overview-industrial Electronics Engineering-Bachelors' Thesis*.

Chy, M.K.A., Masum, A.K.M., Sayeed, K.A.M., & Uddin, M.Z. (2021). Delicar: A smart deep learning based self driving product delivery car in perspective of Bangladesh. *Sensors (Basel)*, *22*(1), 126.

Denoël, V. (2007). *An introduction to reliability analysis*.pp. 1-82. Université de Liège, Belgium.

Firdos, M., Abbas, K., Abbasi, S.A., & Abbasi, N.Y. (2020). Modeling and comparison of maximum likelihood and median rank regression methods with fréchet distribution. *Proceedings on Engineering Sciences*, *2*(2), 159-168.

Ghosh, A., Sufian, A., Sultana, F., Chakrabarti, A., De, D. (2020). Fundamental concepts of convolutional neural network. In: Balas, V., Kumar, R., Srivastava, R. (eds) *Recent Trends and Advances in Artificial Intelligence and Internet of Things*. Intelligent Systems Reference Library (Vol, 172, pp. 519-567). Springer, Cham. https://doi.org/10.1007/978-3-030-32644-9_36.

González, D., Pérez, J., Milanés, V., & Nashashibi, F. (2015). A review of motion planning techniques for automated vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *17*(4), 1135-1145.

Grigorescu, S., Trasnea, B., Cocias, T., & Macesanu, G. (2020). A survey of deep learning techniques for autonomous driving. *Journal of Field Robotics*, *37*(3), 362-386. https://doi.org/10.1002/rob.21918.

Guanetti, J., Kim, Y., & Borrelli, F. (2018). Control of connected and automated vehicles: State of the art and future challenges. *Annual Reviews in Control*, *45*, 18-40. https://doi.org/10.1016/j.arcontrol.2018.04.011.

Hallinan Jr, A.J. (1993). A review of the Weibull distribution. *Journal of Quality Technology*, *25*(2), 85-93.

Hnewa, M., & Radha, H. (2021). Object detection under rainy conditions for autonomous vehicles: A review of state-of-the-art and emerging techniques. *IEEE Signal Processing Magazine*, *38*(1), 53-67. https://doi.org/10.1109/msp.2020.2984801.

Hoole, G. (2013). *The new official k53 manual: Motorcycles, light and heavy vehicles*. Penguin Random House South Africa.

Ignatious, H.A., & Khan, M. (2022). An overview of sensors in autonomous vehicles. *Procedia Computer Science*, *198*, 736-741.

Jo, K., Kim, J., Kim, D., Jang, C., & Sunwoo, M. (2015). Development of autonomous car—Part II: A case study on the implementation of an autonomous driving system based on distributed architecture. *IEEE Transactions on Industrial Electronics*, *62*(8), 5119-5132.

Kossiakoff, A., Biemer, S.M., Seymour, S.J., & Flanigan, D.A. (2020). *Systems engineering principles and practice*. John Wiley & Sons.

Lai, C.D., Murthy, D., & Xie, M. (2006). Weibull distributions and their applications. In *Springer Handbooks* (pp. 63-78). Springer.

Ma, Y., Wang, Z., Yang, H., & Yang, L. (2020). Artificial intelligence applications in the development of autonomous vehicles: A survey. *IEEE/CAA Journal of Automatica Sinica*, *7*(2), 315-329. https://doi.org/10.1109/jas.2020.1003021.

Mackie, T. (2018). Proving liability for highly and fully automated vehicle accidents in Australia. *Computer Law & Security Review*, *34*(6), 1314-1332. https://doi.org/10.1016/j.clsr.2018.09.002.

Matthaei, R., & Maurer, M. (2015). Autonomous driving – a top-down-approach. *at - Automatisierungstechnik*, *63*(3), 155-167. https://doi.org/10.1515/auto-2014-1136.

Ndung'u, N., & Signé, L. (2020). The fourth industrial revolution and digitization will transform africa into a global powerhouse. *Foresight Africa Report*, *5*(1), 1-5.

Paden, B., Cap, M., Yong, S.Z., Yershov, D., & Frazzoli, E. (2016). A survey of motion planning and control techniques for self-driving urban vehicles. *IEEE Transactions on Intelligent Vehicles*, *1*(1), 33-55. https://doi.org/10.1109/tiv.2016.2578706.

Schwarting, W., Alonso-Mora, J., & Rus, D. (2018). Planning and decision-making for autonomous vehicles. *Annual Review of Control, Robotics, and Autonomous Systems*, *1*(1), 187-210. https://doi.org/10.1146/annurev-control-060117-105157.

Sell, R., Leier, M., Rassõlkin, A., & Ernits, J.P. (2018). Self-driving car ISEAUTO for research and education. In *2018 19th International Conference on Research and Education in Mechatronics (REM)* (pp. 111-116). IEEE. Delft, Netherlands.

Shelhamer, E., Long, J., & Darrell, T. (2017). Fully convolutional networks for semantic segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *39*(4), 640-651.

Singh, S., & Saini, B.S. (2021). Autonomous cars: Recent developments, challenges, and possible solutions. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1022, No. 1, p. 012028). IOP Publishing. Rajpura, India.

Sviatov, K., Yarushkina, N., Kanin, D., Rubtcov, I., Jitkov, R., Mikhailov, V., & Kanin, P. (2021). Functional model of a self-driving car control system. *Technologies*, *9*(4), 100. https://doi.org/10.3390/technologies9040100.

Tan, S.Y., & Taeihagh, A. (2021). Adaptive governance of autonomous vehicles: Accelerating the adoption of disruptive technologies in Singapore. *Government Information Quarterly*, *38*(2), 101546.

Uzair, M. (2021). Who is liable when a driverless car crashes? *World Electric Vehicle Journal*, *12*(2), 62. https://doi.org/10.3390/wevj12020062.

Vaicenavicius, J., Wiklund, T., Grigaite, A., Kalkauskas, A., Vysniauskas, I., & Keen, S.D. (2021). Self-driving car safety quantification via component-level analysis. *SAE International Journal of Connected and Automated Vehicles*, *4*(1), 35-45. https://doi.org/10.4271/12-04-01-0004.

Vargas, J., Alsweiss, S., Toker, O., Razdan, R., & Santos, J. (2021). An overview of autonomous vehicles sensors and their vulnerability to weather conditions. *Sensors (Basel)*, *21*(16), 5397. https://doi.org/10.3390/s21165397.

Wu, J. (2017). Introduction to convolutional neural networks. *National Key Lab for Novel Software Technology. Nanjing University. China*, *5*(23), 1-31.

Yan, C., Xu, W., & Liu, J. (2016). Can you trust autonomous vehicles: Contactless attacks against sensors of self-driving vehicle. *Def Con*, *24*(8), 109. https://doi.org/10.1145/1235.

Yeong, J., Velasco-Hernandez, G., Barry, J., & Walsh, J. (2021). Sensor and sensor fusion technology in autonomous vehicles: A review. *Sensors (Basel)*, *21*(6), 2140. https://doi.org/10.3390/s21062140.

Zhao, L., Ichise, R., Liu, Z., Mita, S., & Sasaki, Y. (2017). Ontology-based driving decision making: A feasibility study at uncontrolled intersections. *IEICE TRANSACTIONS on Information and Systems*, *100*(7), 1425-1439.

Zhao, L., Ichise, R., Yoshikawa, T., Naito, T., Kakinami, T., & Sasaki, Y. (2015). Ontology-based decision making on uncontrolled intersections and narrow roads. In *2015 IEEE Intelligent Vehicles Symposium (IV)* (pp. 83-88). IEEE. Seoul, South Korea.