Deakin University

Software Requirements Analysis and Modelling

OnTrack Submission

Research project

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Outcome	Weight
Identify Functional Requirements	♦♦♦♦♦
Logical Models	♦♦♦♦♦
Non-functional Requirements & Constraints	♦♦♦♦♦
Translating Requirements	♦♦♦♦♦
Justify	♦♦♦♦♦

As autonomous vehicles become more integrated into modern transport systems, ensuring their safety is no longer just a technical challenge — it's a societal necessity. Traditional requirement analysis techniques often fall short when applied to safety-critical systems like self-driving cars, which operate in unpredictable, real-world environments. This task is driven by the need to explore and apply more robust approaches, such as Fault Tree Analysis (FTA), Failure Mode and Effects Analysis (FMEA), and System-Theoretic Process Analysis (STPA), to identify, analyze, and mitigate risks early in the design process. By translating these insights into actionable requirements, this project aims to support the development of autonomous systems that are not only functional but fundamentally dependable and safe.

May 25, 2025

Safety Critical System Research: Improving Safety Assurance in Self-Driving Cars: A Study of Risk-Based Requirement Techniques

1. Introduction

Systems classified as safety-critical are ones whose malfunction might have disastrous results, such as fatalities, major property damage, or environmental degradation. These systems are essential to industries like as healthcare, aviation, and, more and more, automotive technology. [1]. Autonomous vehicles (AVs), or self-driving automobiles, are the pinnacle of contemporary safety-critical technologies. To explore areas without the need for human involvement, they rely on intricate integrations of sensors, machine learning algorithms, and control systems. AVs hold promise in lowering human error-related accidents, which are responsible for around 94% of road fatalities. [2]

AV adoption, however, brings with it additional difficulties. Incidents involving prominent AV developers have demonstrated that mishaps can result from malfunctions in perception systems, software bugs, or unanticipated environmental circumstances [3]. These incidents highlight how important it is to have strict safety regulations. A foundation for functional safety in automotive systems is provided by the ISO 26262 standard, which highlights the significance of risk assessment and hazard analysis during the course of the vehicle's lifetime [4].

In this context, ensuring the safety of self-driving cars is paramount. This paper explores the intricacies of AV safety, analyzing the shortcomings of conventional requirement analysis methods and investigating cutting-edge approaches to improve these systems' dependability.

2. Case Study Scenario

During rush hour, picture an autonomous car navigating the busy streets of Central Business District in cities areas. Passengers must be securely transported from their office buildings to their houses via the vehicle, which must navigate congested streets with vehicles, trams, bikes, and pedestrians all moving erratically through crossings.

The operational environment is highly dynamic, with situations like crowded highways, sudden lane closures, uneven road surfaces, and erratic pedestrian movements all changing quickly. The vehicle's systems must rely significantly on sensor fusion- combining camera, radar, and LiDAR data to continually adapt to changing conditions- because traffic lights and signs may occasionally be hidden or damaged.

One of the key functionalities is precision navigation, which guarantees that the vehicle stays on predetermined routes and adapts dynamically to traffic situations in real time. In order to anticipate and proactively address threats, sophisticated collision avoidance systems continually evaluate sensor data. By detecting human motions and reacting quickly, pedestrian detection technology guarantees safety. Even in poorly delineated roads or inclement weather, lane-keeping assistance ensures the car stays on the correct course.

The intricate urban environment of the vehicle makes any malfunction in these systems potentially disastrous. Sensor failures or software mistakes in pedestrian recognition, for instance, may result in severe crashes that injure or kill people. Negligence in navigation or lane-keeping may lead to hazardous circumstances, including crossing the route of an approaching tram or pedestrian zone, which might cause serious injury, legal ramifications, and a general mistrust of autonomous technology.

This situation emphasizes how important it is to use strict, extra requirement analysis methodologies in addition to conventional ones in order to guarantee the dependability and safety of autonomous cars working in strange urban settings.

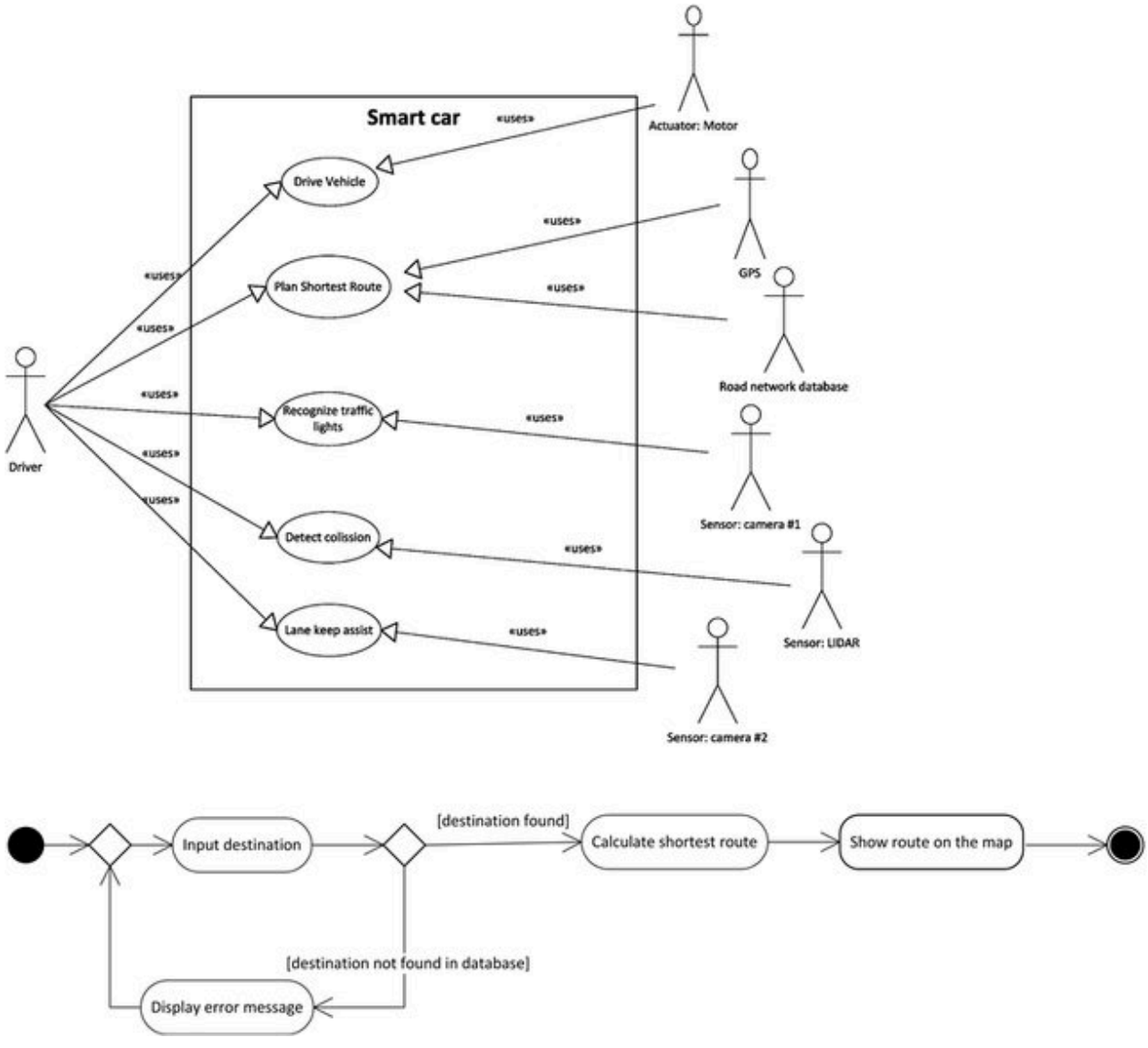

Figure 1: Use-case diagram illustrating core interactions of self-driving car system." [5]

With an emphasis on the autonomous vehicle (Smart car) and its interactions with external actors such as GPS, road network databases, and sensors, the use-case diagram in Figure 1 depicts the fundamental interactions inside a self-driving automobile system. Key functions of the system include driving, shortest-distance planning, traffic signal recognition, collision detection, and lane-keeping support. By starting directives like route input, the human driver communicates with the system. The system's modular design and the importance of real-time sensor integration are shown in the diagram. In order to preserve safety and avoid failure in intricate urban contexts, it highlights the necessity of precisely defining and validating system limits and actor interactions.

3. Problem and Vision Statements

Self-driving automobiles must make judgments in real time without human supervision in dynamic and unexpected surroundings. Multiple sensor inputs, including cameras, LiDAR, and radar, must be seamlessly integrated in order to identify and react to complicated circumstances, such as abrupt pedestrian crossings or unpredictable driving behavior, with accuracy. These sensors are limited, though. Poor illumination and occlusion can affect cameras, and shiny surfaces, fog, or snow can interfere with LiDAR devices. As a result, even little errors or delays in sensor data can result in major malfunctions, including failing to see a pedestrian, straying from a lane, or running into someone. Because of their safety-critical nature, these systems require a sophisticated, risk-aware requirement analysis approach to guarantee system dependability under all operating situations and avoid disastrous results.

The project aims to develop a strong, safety-focused requirements specification framework for self-driving automobiles. Enhancing the system's dependability in actual metropolitan settings is the goal, as these environments are constantly challenged by unforeseen elements including unpredictable drivers, fluctuating weather, and sensor failures. Potential failure spots can be proactively addressed by including sophisticated risk analysis methods, such as fault tree analysis, failure mode analysis, and hazard identification, into the early phases of system design. Reduced accident risk and safe operation of autonomous cars even in unanticipated or deteriorated situations are the ultimate objectives. In addition to supporting the public's confidence in autonomous vehicles, this vision complies with practical safety regulations such as ISO 26262.

4. Challenges with Standard Requirement Techniques

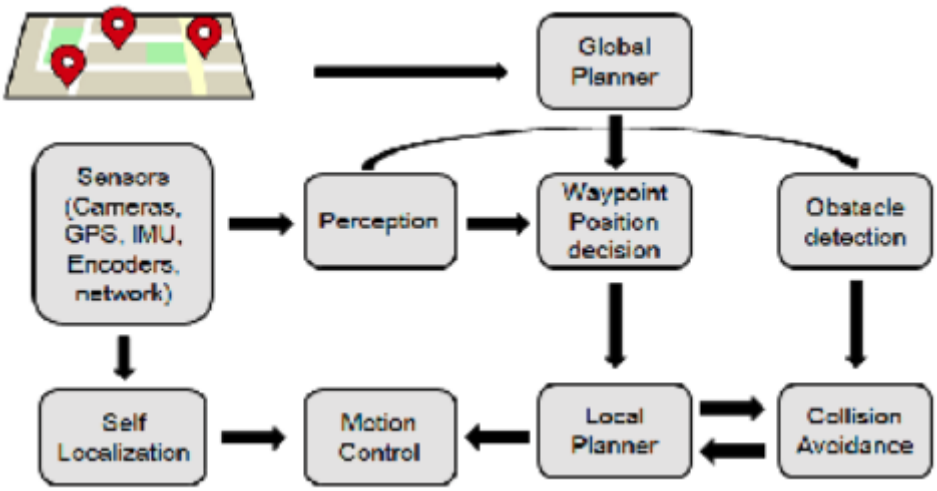

Figure 2: System architecture diagram showing sensors, control systems, and interfaces [19]

A simplified system architecture of a self-driving car is depicted in Figure 2, where a number of sensors (radar, LiDAR, and cameras), control modules, and external data sources cooperate to allow autonomous driving. In order to assess environmental inputs, make choices, and carry out vehicle actions in real time, these systems communicate constantly. One of the main causes of standard requirements engineering methodologies' inability to work in safety-critical situations, such as autonomous automobiles, is their complexity.

Stakeholder interviews, simple UML diagrams, and user stories are examples of standard procedures that are helpful for articulating expected features, but they frequently fall short in identifying hidden hazards or modeling dynamic, unpredictable situations. A use-case diagram might say, for instance, "detect pedestrian", but it won't take into consideration edge circumstances like kids running between parked cars or unexpected obstacles in bad weather. In a similar vein, failure modes that only manifest under coupled hardware-software stress may be missed during interviews. The accuracy required to simulate asynchronous sensor inputs, real-world behavioral uncertainty, and the possible repercussions of delayed or inaccurate system responses is lacking in these conventional methods [1].

In high-risk industries such as medical devices and aircraft, engineers use extra safety analysis methods to overcome these problems. Fault Tree Analysis (FTA) and Failure Mode and Effects Analysis (FMEA) are commonly used methods. FTA helps find the reasons behind system-level problems by mapping how a misread LiDAR sensor could lead to a missed braking event. On the other hand, FMEA is used to find out the ways in which specific components can fail, assess their chances, seriousness and how easy they are to detect and suggest suitable protections [5]. Beyond that, STPA is a new hazard analysis technique that focuses on identifying inadequate control scenarios causing unwanted losses or accidents in complex systems. It is developed based on the STAMP (Systems-Theoretic Accidents Model and Process) model, which considers system control rather than component failure or reliability. [6]

Meanwhile, formal methods provide mathematical rigor for validating control logic, such as Model Checking or formal specification languages like Z notation or the B-Method. These techniques are able to confirm system characteristics such as safety (for example, "the car must never collide with an object") in any condition that could exist [6]. In software-based safety systems, where a single unnoticed fault could cause physical harm or even death, this is particularly crucial.

However these cutting-edge techniques have drawbacks. Both a significant time commitment and a steep learning curve are required. For example, formal modeling may hinder collaboration since it necessitates a high level of mathematical skill and might be challenging for stakeholders who are not technical to comprehend. In contrast, thorough FTA or FMEA assessments might need a lot of resources, especially for large-scale, sensor-rich systems like self-driving cars.

Technique	Limitation	Impact
Fault Tree Analysis (FTA)	Time-consuming for complex systems	Can delay development due to detailed fault tracing
Failure Mode and Effects Analysis (FMEA)	Needs deep domain-specific knowledge	May miss risks if team lacks experience
System-Theoretic Process Analysis (STPA)	Can produce many scenarios; interpretation requires system thinking mindset	May be overwhelming without tool support or structured analysis process
Model Checking	Requires formal modeling & tool expertise	High learning curve for development teams
Z / B Formal Methods	Difficult for non-specialists to interpret	Hinders clear communication with non-technical stakeholders

Table 1: Limitations and trade-offs of advanced safety analysis techniques [5] [6]

5. Proposed Techniques

Designing safe and reliable self-driving systems means going beyond documenting what the system should do- it involves anticipating what could go wrong, understanding why it might happen, and building in defenses. In safety-critical domains, the process of refining requirements is deeply rooted in structured risk analysis. This section outlines how we identify key risks, trace their root causes, and ultimately translate those insights into specific, safety-enhancing system requirements for autonomous vehicles.

5a. Identifying and Classifying Risks

One of the most important initial steps in designing autonomous vehicle (AV) systems for safe and dependable operation is recognizing and categorizing risks. These hazards come from a variety of causes, such as erratic surroundings, malfunctioning parts, and poor system-level judgment.

Sensor and perception failures are one of the main risk categories. LiDAR, radar, and cameras are the tools that AVs use to sense their surroundings, but poor weather, glare, or occlusion can cause readings to be off. It has been demonstrated, for instance, that emergency vehicle lights can disrupt camera-based systems' object recognition skills, raising the possibility of hazard detection failure [7].

The absence of dependable connectivity poses an additional concern. AVs that don't have vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication aren't as aware of the state of the road or other cars' intentions. This restricts their capacity to foresee risks and respond appropriately in intricate traffic situations [8].

Risk is introduced by decision-making difficulties as well. Many autonomous vehicles (AVs) rely on artificial intelligence (AI) systems to make decisions in real time, but because some models are black-box, their behavior may be unpredictable in edge circumstances, such as construction zones or anomalous pedestrian movements [9].

Cybersecurity risks are also becoming a bigger worry. Attackers may alter digital maps or road markings to make AVs behave dangerously. Perception systems may be misled into adopting risky behaviors by such adversarial attacks [10].

Lastly, there are significant concerns associated with mixed traffic settings. AVs must be able to comprehend and adjust to unanticipated actions, such as abrupt lane changes or inability to yield, because human drivers frequently exhibit inconsistent behavior. [11].

5b. Analyse and Classify These Risks

Analyzing and categorizing possible hazards in an autonomous vehicle (AV) system in a systematic manner comes next. This step aids in prioritizing the most important risks- those that need to be addressed right away in the design- and figuring out how they might spread across the system.

Using a risk matrix that assesses three important variables is a commonly used strategy in the automotive industry:

- **Likelihood of Occurrence:** How likely is the risk to materialize in actual operational circumstances?
- **Consequence Severity:** What might happen if the risk materializes? This might be anything from a small navigational mistake to a potentially fatal collision.

- **Controllability:** How simple is it for the system to recognize a failure, mitigate it, or transition to a safe state?

This framework directly aligns with the ISO 26262 Automotive Safety Integrity Level (ASIL) methodology, which uses these three factors to assign a safety classification (A to D), with ASIL D representing the most safety-critical requirements [4].

Classification in safety engineering is strengthened by using Fault Tree Analysis (FTA) and Failure Modes and Effects Analysis (FMEA). The approach involves studying how every element or stage in a system, for example camera overexposure or LiDAR loss, could create a failure that might impact the overall system. A failure is assigned an RPN depending on how severe, how often it happens and how easily it can be detected. Both redesign and careful inspection are important for areas with high RPN scores [12]. With FTA, all contributing causes, including hardware errors and software delays, are discovered beginning with the main failure, in this case, "The vehicle fails to detect a pedestrian." As a result, engineers can easily pinpoint what causes threats to appear and design multiple safeguards to block them [1].

In systems where software behavior plays a central role, additional techniques such as System-Theoretic Process Analysis (STPA) are beneficial. STPA classifies risks not just based on hardware failure but also unsafe control logic - for instance, a late braking command or conflicting steering instructions. Unlike traditional failure-focused methods, STPA models the interaction between components and control flows, which is essential in complex, AI-driven systems like AVs [13].

To make classification more actionable, we group risks into categories such as:

- Perception-related (e.g., sensor failure, object misclassification)
- Planning-related (e.g., incorrect route generation, poor lane-change timing)
- Control-related (e.g., delayed brake actuation, actuator conflict)
- External factors (e.g., unpredictable human drivers, environmental conditions)
- Cybersecurity-related (e.g., spoofed road signs or GPS manipulation)

By combining these analysis techniques with structured classification, we ensure that safety priorities are not based on intuition or general concern, but grounded in traceable, validated risk profiles.

5c. Root Cause Analysis with FTA and FMEA

Once critical risks are identified, we use Fault Tree Analysis (FTA) to trace their possible causes. FTA begins with a top-level event - say, “the vehicle fails to stop at a red light” - and maps out all potential underlying causes: sensor lag, faulty object detection, or delayed actuator response. This tree-based approach provides a clear, logical structure for understanding how multiple small issues can cascade into a critical failure.

In contrast, Failure Modes and Effects Analysis (FMEA) is a bottom-up approach that examines individual components. For example, the radar system may have a failure mode where it returns inconsistent range values. FMEA assigns each failure mode a Risk Priority Number (RPN) based on severity, likelihood, and detectability. High-RPN items are prioritised for design revision or redundancy.

Both techniques are supported under ISO 26262, the international safety standard for automotive systems, and are widely used in functional safety assessments [2].

5d. Risk Mitigation Strategies

For risk identification and classification to be worthwhile, the AV system must be built to address and quell those risks. This is the point where ways to deal with risk are brought in. To reduce risks for self-driving cars, a flexible and multilayered approach uses multiple sensors, prevents failures and keeps an eye on issues in real time.

Through redundancy, critical systems can keep operating when some parts of them fail. When working with perception, integrating LiDAR, radar and cameras can make up for the weaknesses of an individual sensor. Although a camera is sensitive to bad and bright light, LiDAR can still deliver precise information about depth. By comparing data from several sensors, we can make the results more accurate and lower the risk of incorrectly identifying objects [14], [15].

Fail-safe protocols move the system to a known good state as soon as a critical fault is noticed. If the system detects that its position is not trusted due to GPS problems or inconsistencies in the map, it activates a controlled decline in speed and a safe stop. ISO 26262 depends heavily on this idea when considering how systems should behave during hazardous scenarios [4].

System monitoring and detecting anomalies in real time create the third way to protect systems. Checking data from performance metrics allows AV systems to detect signs of unusual behavior early. If the system finds that obstacle detection is taking more time or the measurements from sensors differ unexpectedly, it can change its driving style, enter cautious mode or communicate with supervising teams away from the vehicle [16].

Rather than being all separate, mitigation plans all work together, shown in Figure 3. Risks are used to shape extra requirements which then affect the way the system will be monitored and controlled. Implications of the system’s activities clarify how to further improve the model and safety controls for ongoing improvement.

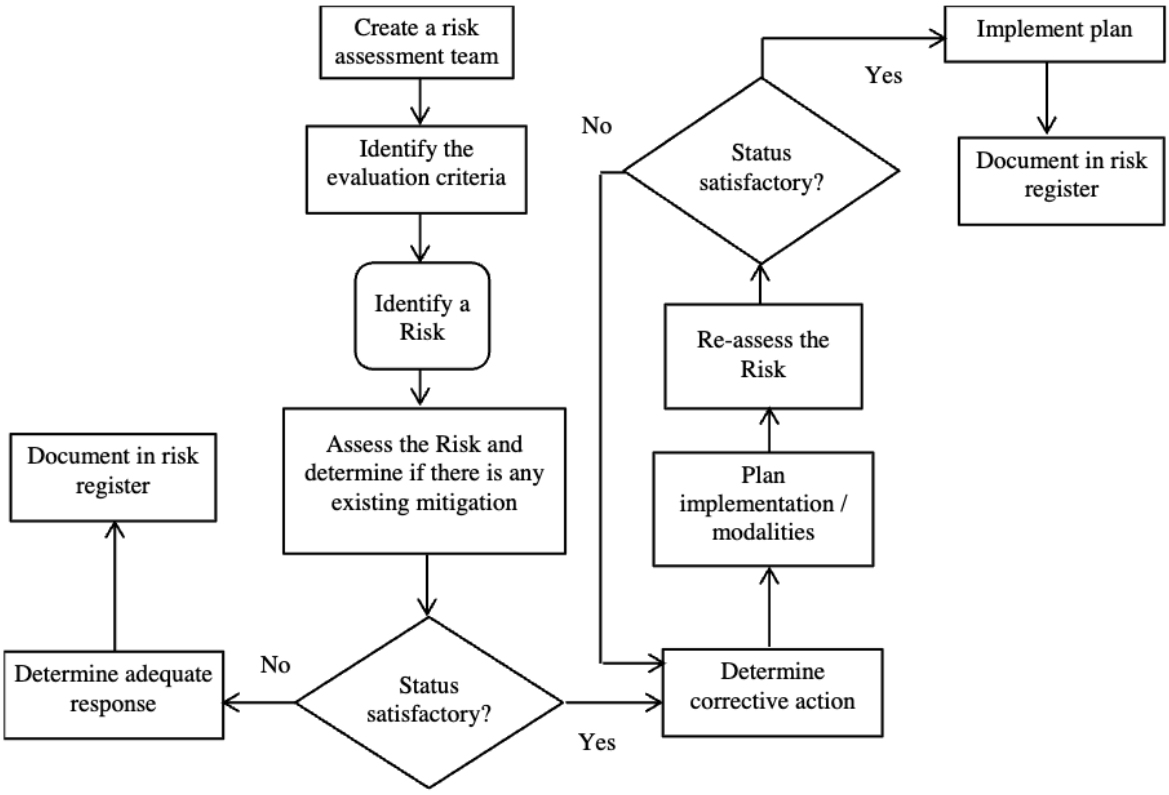

Figure 3: Risk Assesment Process flow diagram demonstrating supplemental requirement analysis and risk mitigation procedures [17]

By integrating these layered approaches, AV developers can build systems that are not only capable of executing tasks but are also prepared to gracefully degrade and recover when facing uncertainty or component failure- hallmarks of a mature safety-critical system.

5e. Translating Risks into Requirements

Identifying and analyzing risks is followed by ensuring that the system responds to them in practice- that is, through well-defined design actions- rather than only in theory. This entails transforming learnings from the FTA and STPA into useful, safety-focused specifications that influence how the car responds in unexpected situations.

Risk-informed requirements, as opposed to standard functional requirements, which typically outline what the system should perform in ideal circumstances, concentrate on how the system should respond in less-than-ideal circumstances, such as when a sensor malfunctions or when the road infrastructure is unclear.

To help visualize where risks can originate, Figure 4 (adapted from Happe et al. [1]) shows the Operational Design Domain (ODD) and how different elements - like the environment, vehicle system, and driver - interact. It highlights where things can break down:

whether it's a sensor missing a road sign, the driver not being ready to take control, or the system operating in a situation it wasn't designed for.

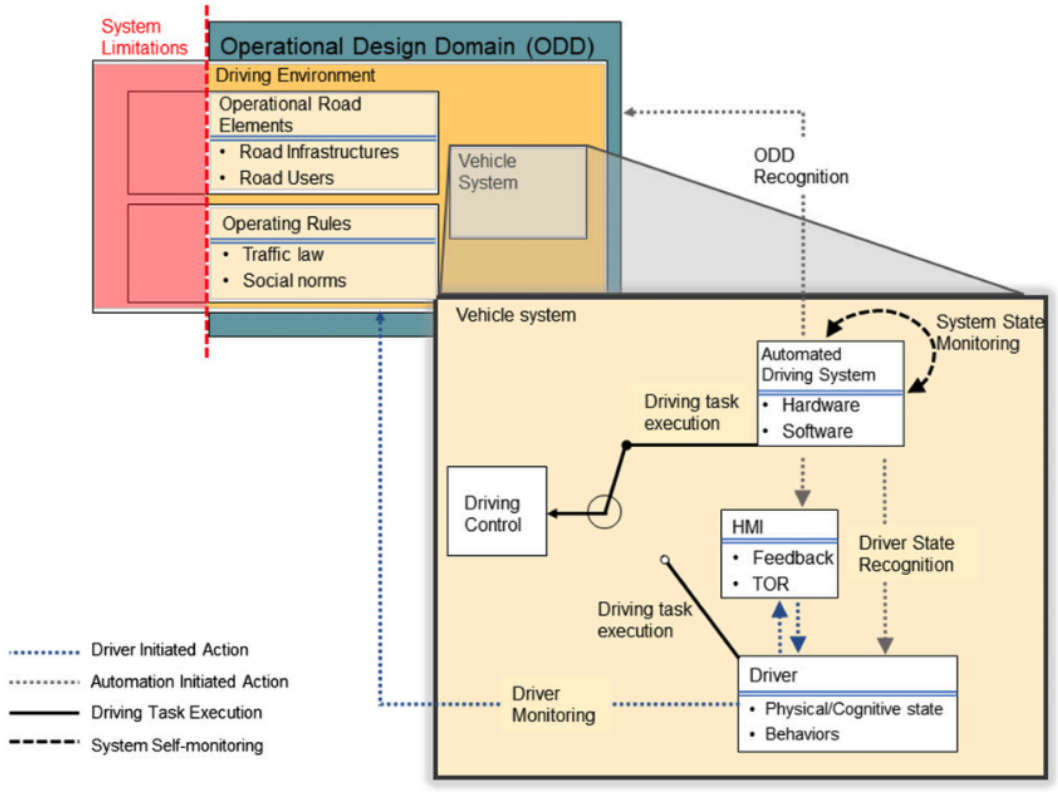

Figure 4: Operational Design Domain (ODD) structure for automated driving, showing how system limitations, driving context, and human input connect. Adapted from [18].

Using this model as a guide, here are a few risk-driven requirements we propose, based on the earlier analysis:

R1. If two or more core sensors (e.g., LiDAR and radar) report conflicting obstacle data, the vehicle must come to a controlled stop within 2 seconds.

R2. If GPS accuracy drops below 2.5 meters for more than 5 seconds, the planner must switch to a conservative backup route.

R3. Before autonomous mode is deactivated, the system must confirm the driver is ready to take over - using checks like eye-tracking or hand position on the wheel.

R4. If the system can't detect road markings or signs with at least 90% confidence for more than 3 seconds, it should slow down and alert the driver or support system.

R5. If V2X connectivity is lost, the vehicle must restrict advanced maneuvers like lane changes and reduce speed to account for reduced awareness.

These are safety assurances derived from understanding the potential locations of actual failures, not things that customers might want during an interview. Additionally, AVs are safer and more reliable because of their proactive design.

By directly integrating these sorts of needs into the system and linking them to certain hazards, we make sure the car is not only operating efficiently when everything is working well but also remaining safe in the event of an emergency.

6. Requirements Specification

The following table outlines 11 risk-informed requirements derived from the hazard and risk analysis process. Each requirement addresses specific safety concerns identified in earlier sections, aiming to improve the system's resilience to sensor failures, control delays, environmental uncertainty, and user interactions. These requirements reflect not just what the system should do, but how it should respond when things go wrong.

ID	Description	Priority	Rationale	Verification Method
R01	Vehicle must come to a controlled stop within 2 seconds if obstacle detection confidence drops below threshold.	High	Prevents collisions when system is unsure of surroundings.	Simulation and sensor-fusion test logs
R02	Planning module must switch to conservative route when GPS accuracy drops below 2.5m for 5+ seconds.	High	Ensures safe navigation under degraded localization.	Real-world degraded GPS scenario testing
R03	Before deactivating autonomous mode, the system must verify driver readiness via eye tracking.	High	Reduces risk during handover to distracted or unresponsive drivers.	Driver-state recognition test cases
R04	Pedestrian detection must be cross-validated using at least two sensor modalities (e.g., LiDAR and camera).	High	Prevents misclassification errors in complex environments.	Sensor fusion validation and benchmarking

R05	When road infrastructure cannot be confidently detected for 3+ seconds, vehicle must slow and activate hazard lights.	Medium	Addresses scenarios with missing or obscured signs and markings.	Edge-case testing in occluded environments
R06	System must log sensor conflicts or anomalies within 1 second and trigger safe-mode if unresolved.	High	Enables early fault detection and response.	Event logs and system fault injection
R07	V2X communication loss must disable lane changes and reduce speed by 20%.	Medium	Maintains conservative driving when environment data is limited.	Connectivity loss test scenarios
R08	Automated braking system must respond within 100 ms of pedestrian detection in urban zones.	High	Timely braking response is essential in dense traffic areas.	High-speed camera & sensor response testing
R09	System must perform a hardware self-check on startup and alert if any sensor fails.	High	Ensures AVs only operate when all components are functional.	Startup diagnostics and fault tests
R10	Driver override commands (e.g., brake press) must instantly override automated controls.	High	Guarantees safety and driver authority during emergencies.	HMI testing under manual intervention
R11	Road condition anomalies (e.g., potholes or debris) must be flagged in the map system within 30 seconds.	Low	Supports ongoing learning and environment updates.	Crowdsourced map feedback testing

These requirements aim to make the vehicle smarter in how it handles risk- by not just detecting threats, but acting decisively when uncertainty is high. Collectively, they reflect a system that's prepared for real-world complexity and designed with safety at its core.

7. Conclusion

This report explored the challenges of ensuring safety in autonomous vehicle systems and highlighted the limitations of traditional requirement techniques. Through structured analysis methods such as FTA, FMEA, and STPA, we identified critical risks, traced their root causes,

and translated them into actionable, safety-focused requirements. These supplemental techniques go beyond surface-level design, addressing how the system should behave under uncertainty or failure. By integrating risk analysis into the requirement engineering process, we strengthen the system's resilience and contribute meaningfully to the development of safer, more reliable autonomous vehicles.

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