Exploring Safety Metrics for Driving Assessment and Human-Machine Interaction in Level-1 and Level-2 Automated Vehicles: A Comprehensive Theoretical Review

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ABSTRACT

This report delves into the intricate landscape of safety metrics concerning Level 1 and Level 2 automated vehicles, synthesizing recent literature to illuminate critical aspects of driving assessment and human-machine interaction. Understanding these factors serves as a cornerstone in establishing comprehensive metrics and regulatory frameworks essential for the safe operation of these vehicles. The review meticulously examines various facets of driving assessment and human-machine interaction, encompassing their significance, prevalent challenges, existing systems, and methodologies proposed by diverse studies for comprehensive calculation and analysis. Emphasis is placed on discerning the nuanced dimensions of these factors to facilitate informed decision-making in shaping regulations and safety protocols.

Moreover, the report meticulously identifies research gaps, shedding light on areas necessitating further exploration. Drawing upon the collated literature, conclusive reflections underscore the pivotal need for holistic safety metrics that consider multifaceted aspects of automated vehicle operations, thereby contributing to the evolution of safer and more efficient transportation systems. This comprehensive review not only consolidates current knowledge but also steers attention towards crucial areas warranting deeper investigation, culminating in a roadmap for advancing safety metrics and regulations for Level 1 and Level 2 automated vehicles.

Key words: Safety metrics, driving assessment, human-machine interaction, regulatory framework

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1 INTRODUCTION

In the expanding and ever-evolving domain of transportation, one of the major concerns world-wide is road safety. Its significance transcends borders, demanding a concerted and urgent effort toward innovative solutions from all corners of society. Despite the considerable strides witnessed in vehicle technology, the lamentably high toll of fatalities resulting from on-road collisions continues to cast a somber pall over societies worldwide. In response to this ongoing challenge, the automotive sector finds itself at the forefront of a transformative revolution, embracing groundbreaking safety technologies collectively referred to as "active safety" and "driving automation" features. These advancements aren't merely incremental; they signify a paradigm shift wherein vehicles don't just alert human drivers but actively intervene in potentially hazardous situations [1].

The potential and promise held by these technological strides are vast, offering a glimpse into a future where collisions are not only less frequent but also less severe [2]. However, as vehicles veer increasingly toward automation, a pivotal question surfaces: what concrete impact do these rapidly evolving technologies have on the broader spectrum of road safety [3]? The emergence of features designed to significantly reduce or potentially eliminate the human role in the dynamic driving task marks an inflection point in transportation. Yet, the true scope and implications of this revolutionary shift remain intricate and, to a significant extent, uncharted.

The stark reality is that human errors contribute to approximately 90% of road accident fatalities, encapsulating distractions, fatigue, traffic rule violations, and flawed judgments [4] [5] [6] [7]. Acknowledging this, the integration of automation into the driving task emerges as a critical opportunity to alleviate these errors, thereby enhancing road safety. However, the potential benefits extend far beyond the realm of error reduction; they encompass broader improvements in accident costs, productivity, mobility, and overall convenience.

Yet, this transition to automation brings forth a web of intricacies and challenges. Vehicles outfitted with an array of active safety and driving automation features pose a myriad of complexities for consumers, regulators, and industry stakeholders alike. The diverse nature of these features, coupled with the intricate human-machine interaction (HMI), complicates the understanding of their collective safety impact.

The automotive sector's rapid innovation is evidenced by the plethora of safety features ranging from warning systems alerting drivers to potential hazards to advanced interventions significantly improving road safety [1]. However, the impacts of these features are anything but uniform due to variations in feature types and developer approaches. This diversity leads to a lamentable lack of standardization in safety metrics and evaluation criteria.

Human-machine interaction (HMI) emerges as a critical focal point as automation becomes more ingrained in driving tasks, necessitating seamless interaction between vehicles and their human occupants. Yet, this interaction introduces complexities contributing to the existing knowledge gap concerning safety implications (NHTSA). As human drivers transition from active control to passive monitoring, understanding their interaction with automated systems becomes a cornerstone in evaluating overall safety impact.

Navigating this intricate landscape calls for the establishment of standardized safety evaluation metrics, serving as benchmarks for assessing diverse driving automation features (NHTSA). Ongoing efforts toward standardization, led by organizations such as the National Highway Traffic Safety Administration, strive to craft automated vehicle occupant safety standards for a comprehensive and unified approach to safety assessment.

Simultaneously, the pivotal roles assumed by driving assessment metrics and human-machine interaction metrics in evaluating the performance, efficiency, and safety of Level 1 and Level 2 automated vehicles cannot be overstated [8] [9]. These metrics offer extensive insights into system capabilities and limitations, enabling meticulous identification and rectification of areas for enhancement and optimization [10]. Their standardization ensures effortless comparison and identification of areas needing improvement or attention [11].

In essence, the strategic utilization of these metrics propels the development of automated vehicles, bridging traditional driving mechanisms with the future of transportation. Their vast potential drives continuous evolution, reshaping the modern transportation landscape by ensuring unparalleled performance, safety, and efficiency [9] [8]. This convergence of safety technologies, metrics, and regulatory efforts forms the bedrock of a transformative automotive future, promising safer, more efficient, and innovative transportation systems that will revolutionize how we perceive and interact with the roads of tomorrow.

2 DRIVING ASSESSMENT METRICS

Driving Assessment metrics are a crucial component in evaluating the performance and effectiveness of automated vehicles. In Level 1 automated vehicles, these metrics are defined parameters that help enhance safety measures by analyzing various aspects such as the vehicle's ability to detect potential hazards, its responsiveness to real-time traffic situations, and its adherence to traffic rules. In Level 2 automated vehicles, the metrics play a vital role in monitoring driver engagement, assessing the reliability of the automated system, and evaluating the driver's performance when taking over manual control. However, the implementation of driving assessment metrics faces challenges in terms of standardization, data collection and analysis, and integration with vehicle systems. To overcome these challenges, future developments in driving assessment metrics aim to leverage advancements in sensor technology, incorporate artificial intelligence and machine learning applications, and foster collaboration with regulatory bodies. Through comprehensive analysis and evaluation, driving assessment metrics contribute to the continuous improvement and advancement of automated vehicles, ensuring their safety and reliability on the roads.

2.1 IMPORTANCE OF DRIVING ASSESSMENT METRICS

Driving Assessment Metrics play a crucial role in the development and evaluation of Level 1 and Level 2 Automated Vehicles. These metrics enable a comprehensive assessment of various aspects related to driving performance, and safety. By measuring and analyzing key parameters, such as driver engagement, system reliability, and transition to manual control, these metrics provide valuable insights for enhancing the overall efficiency and effectiveness of automated driving systems.

The importance of Driving Assessment Metrics lies in their ability to quantitatively evaluate the performance of automated vehicles and identify areas for improvement. These metrics serve as objective indicators of the vehicle's capabilities, allowing for a standardized comparison across different systems.

In conclusion, Driving Assessment Metrics are essential tools for assessing and improving the performance, and safety in automated vehicles. By providing objective and standardized measurements, these metrics contribute to the ongoing development and advancement of automated driving technology.

2.2 CHALLENGES IN IMPLEMENTING DRIVING ASSESSMENT METRICS

Implementing driving assessment metrics in automated vehicles presents several challenges. Firstly, standardization of metrics is necessary to ensure consistency and comparability across different vehicle models and manufacturers. This requires establishing common criteria and performance measures for evaluating driving performance.

Secondly, data collection and analysis pose challenges in assessing driving behavior and performance. Automated vehicles generate a vast amount of data that needs to be effectively collected, processed, and interpreted. This requires the development of sophisticated algorithms and analytics capabilities to extract meaningful insights from the data.

Another challenge is the integration of driving assessment metrics with vehicle systems. The metrics should seamlessly integrate with the vehicle's sensors, control systems, and communication networks to provide real-time monitoring and feedback. This requires close collaboration between automotive engineers and technology providers.

Overall, addressing these challenges is crucial for the successful implementation of driving assessment metrics in Level 1 and Level 2 automated vehicles. Overcoming these obstacles will help enhance the safety, performance, and reliability of automated driving systems.

2.3 STANDARDIZATION OF METRICS

Standardization of metrics is a critical aspect of developing effective driving assessment systems for Level 1 and Level 2 automated vehicles. By establishing standardized metrics, it becomes possible to compare and evaluate the performance of different vehicles and systems in a consistent and reliable manner. This ensures that assessments are based on objective and comparable data, allowing for meaningful analysis and decision-making. Standardized metrics also facilitate the development of industry-wide benchmarks, enabling manufacturers to set performance targets and track improvements over time. However, achieving standardization poses challenges due to the complexity and variability of driving scenarios, as well as the evolving nature of automation technology. Collaboration among stakeholders, including vehicle manufacturers, researchers, and regulatory bodies, is crucial in establishing consensus on metrics and their measurement methodologies. Additionally, continuous refinement and adaptation of metrics are necessary to keep pace with advancements in sensor technology and the integration of artificial intelligence and machine learning applications. Overall, standardization of driving assessment metrics is essential for the safe and effective deployment of Level 1 and Level 2 automated vehicles.

2.4 SAFETY ENVELOPE AND SAFETY METRICS

The safety envelope refers to the range of operating conditions within which automated vehicles can function safely and effectively, assessed through safety envelope metrics that offer quantitative measures to evaluate their performance and reliability. For Level 1 vehicles, the evaluation focuses on the vehicle's ability to maintain control within specified speed and environmental limits. Conversely, Level 2 vehicles require more advanced metrics to assess their handling of complex driving scenarios and their ability to transition safely between automated and human control. Defining these safety envelope metrics is critical for the secure deployment and operation of automated vehicles, addressing the challenges and limitations associated with their implementation [12] [13] [14].

2.4.1 IMPORTANCE OF SAFETY ENVELOPE METRICS

Safety envelope metrics are fundamental in the development and implementation of both Level 1 and Level 2 automated vehicles. These metrics serve as a means to assess and quantify the boundaries within which these vehicles can operate safely and effectively [12]. By defining and measuring these metrics, researchers and engineers can gain valuable insights into the capabilities and limitations of automated vehicles.

The importance of safety envelope metrics lies in their ability to provide a standardized framework for evaluating the performance and safety of automated vehicles [13]. These metrics allow for objective comparisons between different vehicles and technologies, enabling informed decision-making in the development process. They also play a vital role in ensuring the regulatory compliance of automated vehicles, as they provide measurable criteria to assess whether a vehicle is operating within its intended safety envelope [15].

However, defining and establishing safety envelope metrics for Level 1 and Level 2 automated vehicles presents several challenges. The complexity of the tasks performed by these vehicles, as well as the dynamic nature of real-world driving scenarios, make it difficult to develop comprehensive and universally applicable metrics. Additionally, the uncertain and evolving nature of technology and regulations further complicates the process.

Despite these challenges, there is a growing need for standardized safety envelope metrics to guide the development and deployment of automated vehicles [12]. By addressing these challenges and refining the metrics, researchers, manufacturers, and regulators can work together to ensure the safe and efficient integration of automated vehicles on our roads.

2.4.2 METRICS BASED ON SAFETY ENVELOPE

A. MINIMUM SAFE FOLLOWING DISTANCE:

The minimum safe following distance stands as a critical component within the safety envelope for both Level 1 and Level 2 automated vehicles [16]. This metric defines the crucial space that must be maintained between vehicles to ensure their smooth and secure operation.

For Level 1 vehicles, which offer limited automated assistance, establishing the safety envelope and its associated metrics proves challenging due to varying levels of driver involvement [13].

In contrast, Level 2 vehicles, with higher automation, consider numerous factors when determining their safety envelope. These factors encompass maximum allowable speed and the influence of diverse external and internal factors [17].

While noticeable differences exist in safety envelope metrics between Level 1 and Level 2 vehicles, there are significant similarities. One such commonality is the absolute necessity of maintaining a minimum safe following distance, crucial for passenger and driver safety [18].

Defining these metrics is intricate, relying heavily on real-world scenarios and demanding standardized approaches.

Looking ahead, future advancements should focus on refining safety envelope metrics, integrating them seamlessly into regulatory frameworks to ensure the safe deployment of automated vehicles. This integration will instill confidence in drivers and passengers while nurturing the evolution of automated vehicle technology [19].

B. MAXIMUM ALLOWABLE SPEED

The maximum allowable speed stands as a pivotal factor in delineating the safety envelope for both Level 1 and Level 2 automated vehicles [17]. This metric significantly influences the overall safety and performance of these vehicles, directly impacting their ability to detect potential hazards and maintain control and stability in varying driving conditions.

Defining the maximum allowable speed for automated vehicles is intricate and involves considering multiple factors, including road conditions, traffic patterns, and the capabilities of vehicle sensors and control systems [20]. This complexity further differs between Level 1 and Level 2 automated vehicles due to their differing levels of automation and driver engagement.

Accurately defining this metric is crucial for optimizing the safety and efficiency of automated vehicles on the road [21]. Understanding and appropriately setting the maximum allowable speed contribute significantly to enhancing the vehicles' safety measures and their performance in diverse driving scenarios.

2.4.3 METHODS PROPOSED FOR CALCULATING SAFETY ENVELOPE METRICS

In the domain of automated vehicles, the establishment and assessment of safety envelope metrics play an indispensable role in ensuring the safe operation and interaction of vehicles on roadways. This section delves into the fundamental concepts and methodologies associated with safety envelope metrics.
The concept of the Safe Longitudinal Distance, as proposed by Shalev-Shwartz et al [22], pertains to the safe spacing between two vehicles traveling in the same direction. This metric defines a distance that ensures safety concerning the response time ρ and the vehicles' acceleration and braking capabilities. Specifically, it guarantees that a trailing vehicle (cr) will not collide with the leading vehicle (cf) if the latter performs a maximum braking (amax,brake) and the former accelerates within a specified threshold (amax,accel) during the response time ρ. Furthermore, cr must subsequently brake by at least amin,brake until a complete stop to prevent collision with cf. This formulation serves as a crucial guideline in determining safe distances between vehicles on the road, contributing to collision prevention strategies in automated driving systems.

$$d_{\min} = \left[v_r\,\rho + \frac{1}{2} a_{\max,\text{accel}}\,\rho^2 + \frac{(v_r + \rho\, a_{\max,\text{accel}})^2}{2 a_{\min,\text{brake}}} - \frac{v_f^2}{2 a_{\max,\text{brake}}} \right]_+$$

Additionally, the Minimum Safety Envelope (MSE), detailed by Como, S. and Wishart, J. [15], constitutes a pivotal metric in evaluating the potential risk of collisions between a subject vehicle and a lead vehicle. MSE defines the minimum longitudinal and lateral distance that the subject vehicle should maintain with the lead vehicle to prevent being the cause of a collision. It establishes predetermined safe thresholds, and a violation of this metric occurs if the measured MSE falls below these predefined minimum safe distances when both vehicles are moving in the same direction. By considering both longitudinal and lateral separation, the MSE metric offers a comprehensive assessment tool to ensure safe vehicle spacing and to avoid hazardous situations on the road, especially in the context of automated vehicle scenario navigation. The equations for MSE violation defined by Como, S. and Wishart, J. [15] are as follows:

$$\text{MSEV}' = \begin{cases} 1 & \text{if } d^{lat} < d_{min}^{lat} \wedge d^{long} < d_{min}^{long} \\ 0 & \text{else} \end{cases}$$

$$\text{MSEV} = \begin{cases} 1 & \text{if } MSEV' = 1 \wedge \text{Originated by SV} \\ 0 & \text{else} \end{cases}$$

2.5 LANE STABILITY AND CONTROL

Lane Stability and Lane Control are crucial aspects in Level 1 and Level 2 Automated Vehicles. In order to understand their significance, the definitions of Lane Stability and Lane Control need to be explored.

Lane Stability refers to the ability of an automated vehicle to maintain its intended path within a lane without unnecessary movements or deviations. It involves keeping the vehicle centered within the lane, even in the presence of external factors that may try to displace it [23].

Lane Control, on the other hand, encompasses the capability of an automated vehicle to actively steer and navigate within the boundaries of a lane. It involves the vehicle's ability to accurately follow road markings and adjust its trajectory when necessary [24].

These two concepts are crucial for the safe operation of automated vehicles and are influenced by various challenges [25]. These challenges include environmental factors, road conditions, and vehicle dynamics. Understanding these challenges is key to developing effective lane departure warning systems, lane keeping assist systems, and automated lane centering systems.

Furthermore, safety considerations such as collision avoidance, emergency maneuvers, and interaction with other road users need to be addressed in order to minimize the risk of accidents and ensure the overall safety of both the automated vehicle and its surroundings [26].

Finally, the regulatory framework and standards governing Level 1 and Level 2 Automated Vehicles need to be examined to ensure compliance and to explore future developments [23].

In conclusion, this section provides an insight to the concepts of Lane Stability and Lane Control in Level 1 and Level 2 Automated Vehicles, highlighting their definitions and the challenges they face. It also sets the stage for further exploration of lane departure warning systems, lane keeping assist systems, automated lane centering systems, and the regulatory framework and standards.

2.5.1 CHALLENGES IN LANE STABILITY AND CONTROL

2.5.1.1 ENVIRONMENTAL FACTORS

Environmental factors play a critical role in ensuring lane stability and control in level 1 and level 2 automated vehicles. These factors encompass various elements such as weather conditions, lighting conditions, and the presence of obstacles or road debris. Adverse weather conditions like heavy rain or snow can impact the vehicle's ability to maintain lane stability, while poor lighting conditions can hinder the vehicle's perception of lane markings. Additionally, the presence of obstacles or debris on the road can pose challenges for lane control. Therefore, it is crucial for automated vehicles to adapt to these environmental factors through advanced sensor technologies and intelligent algorithms to ensure safe and efficient lane stability and control.

2.5.1.2 ROAD CONDITIONS

Different road conditions, such as wet, icy, or uneven surfaces, can significantly impact the vehicle's ability to maintain its intended path within the lane. These conditions can affect the tire traction, leading to reduced grip and potential loss of control. Additionally, variations in road markings, visibility, and surface quality can also pose challenges for automated systems in accurately perceiving lane boundaries and adjusting the vehicle's trajectory. Therefore, it is essential for automated vehicles to possess robust sensor and control systems that can effectively adapt to and navigate through various road conditions, ensuring safe and stable lane keeping performance.

2.5.1.3 VEHICLE DYNAMICS

Understanding the dynamics of the vehicle is essential in ensuring safe and stable navigation within a lane. Factors such as the vehicle's acceleration, deceleration, and lateral movement affect its ability to maintain stability and control within the designated lane. By analyzing and optimizing these dynamics, automated systems can make informed decisions to keep the vehicle within the lane boundaries, mitigating any potential risks or deviations.

2.5.2 METRICS FOR EVALUATING LANE STABILITY AND CONTROL VIOLATION

The assessment of lane stability and control violations in automated vehicles stands as a critical endeavor in ensuring their safe and efficient operation on roadways. Diverse metrics have emerged as essential evaluative tools, offering insights into various aspects of vehicle behavior crucial for maintaining lane integrity and maneuvering accuracy. Foremost among these metrics is the concept of Lane Deviation [27]. This parameter quantifies the distance between the vehicle's center and the lane center. Lane deviation is often evaluated using sensors like cameras or lidars capable of detecting lane markings, providing insights into the vehicle's lane-keeping performance and potential lane change maneuvers. Defined as the root mean square error (RMSE) of the lane deviation over a specified time interval or distance traveled, it serves as a foundational measure for assessing the vehicle's spatial alignment within its designated lane.

Complementing lane deviation assessment, Lateral Acceleration [28] emerges as a pivotal metric, elucidating the rate of change of the vehicle's lateral velocity. High lateral acceleration signifies rapid directional shifts, which might introduce discomfort or instability for passengers and other road users. Employing accelerometers or gyroscopes to monitor vehicular motion, the lateral acceleration metric captures the maximum absolute value of lateral acceleration over a designated time or distance.

Moreover, Yaw Rate [29] assumes significance, portraying the rate of change in the vehicle's heading angle. Elevated yaw rates signify substantial alterations in the vehicle's orientation, potentially leading to discomfort or instability. Measured via gyroscopes or magnetometers capable of detecting vehicular rotation, the yaw rate metric encapsulates the maximum absolute value of yaw rate over a defined time or distance.

Additionally, the Steering Angle metric [29] serves as a valuable indicator, reflecting the angle of the steering wheel or front wheels concerning the vehicle's longitudinal axis. Substantial steering angles signify extensive steering inputs by either the driver or the automated system, indicating the complexity or challenge associated with lane change maneuvers. Tracked through potentiometers or encoders monitoring wheel or steering wheel positions, the steering angle metric captures the maximum absolute value of steering angle over a specified time or distance.

These metrics collectively offer a comprehensive framework for evaluating lane stability and control violations in automated vehicles, enabling a nuanced understanding of vehicular behavior within designated lanes. Leveraging insights from various sensors and measurement tools, these metrics contribute significantly to enhancing safety protocols and optimizing the performance of automated driving systems.

2.5.3 LANE DEPARTURE WARNING SYSTEMS

Lane Departure Warning Systems (LDWS) are crucial components of Level 1 and Level 2 automated vehicles [30]. LDWS aim to enhance lane stability and control by promptly alerting the driver when the vehicle deviates from its intended lane. These systems utilize various sensors, such as cameras or infrared sensors, to continuously monitor the vehicle's position within the lane [31]. Upon detecting a potential lane departure, LDWS issue audible or visual warnings, prompting corrective action from the driver [32].

The benefits of LDWS are extensive, including improved safety and reduced accident risks [33]. By notifying the driver about possible lane departures, LDWS help prevent unintended lane changes that could result in collisions or accidents [30]. Furthermore, LDWS assist in reducing driver fatigue and inattentiveness by offering additional support and maintaining awareness of the vehicle's position on the road [33].

Nevertheless, LDWS come with limitations that require consideration [30]. These systems may not consistently detect lane departures in scenarios where road markings are faded or obscured [30]. Additionally, false alarms might occur if the system misinterprets other road features as lane departures [32]. It is crucial for drivers to be aware of these limitations and not overly rely on LDWS, as they are designed to assist rather than replace the driver's responsibility for safe lane control [31].

2.5.4 LANE KEEPING ASSIST SYSTEMS

Lane Keeping Assist Systems (LKAS) serve as pivotal components in level 1 and level 2 automated vehicles [34]. These systems rely on a variety of sensors and actuators to aid vehicles in maintaining their position within a lane. Their primary function involves providing corrective steering inputs when the vehicle starts to deviate from its lane, thereby significantly enhancing lane stability and overall lane control [35].

LKAS offer numerous advantages, notably reducing the risk of lane departure and potential collisions, particularly in scenarios where drivers might be distracted or fatigued [34]. Moreover, these systems alleviate driver workload and enhance comfort by assisting in steering tasks.
However, inherent limitations are associated with LKAS that necessitate careful consideration [36]. Environmental conditions like heavy rain, snow, or fog can impair sensor visibility, impacting the system's performance. Similarly, inaccuracies can arise due to poorly marked or damaged lanes. Furthermore, complex driving scenarios requiring swift decision-making or precise maneuvers can pose challenges to LKAS.

Addressing these limitations requires advancements in sensor technology and algorithms [37]. Additionally, improving human-machine interaction, integrating driver monitoring systems, and establishing clear regulatory frameworks for LKAS are crucial steps toward ensuring the safe and reliable execution of lane stability and control in automated vehicles.

2.5.5 AUTOMATED LANE CENTERING SYSTEMS

Automated Lane Centering Systems (ALCS) play a critical role in ensuring lane stability and control in Level 1 and Level 2 automated vehicles. These systems utilize advanced sensors and algorithms to precisely keep the vehicle in the center of the lane. By continuously monitoring the lane markings and adjusting the steering inputs, ALCS enhances the vehicle's lane-keeping capabilities. The benefits of ALCS include improved safety, reduced driver fatigue, and increased comfort. However, there are limitations to be considered, such as the inability to handle complex road conditions, reliance on clear lane markings, and challenges in handover between automated and human control. To ensure effective human-machine interaction and safety, driver monitoring systems and clear guidelines for control transition are necessary. Overall, ALCS plays a crucial role in achieving lane stability and control in automated vehicles, but further advancements and regulatory standards are needed to ensure their safe and reliable implementation.

2.6 COLLISION INCIDENTS

This section explores various potential incidents that could occur with these types of vehicles. Specifically, it delves into collision scenarios for Level 1 Automated Vehicles, such as rear-end collisions due to inadequate braking and side collisions during lane changes. It also covers Level 2 Automated Vehicles, including failure to detect pedestrians in crosswalks and rear-end collisions due to sudden vehicle deceleration. The aim of this section is to analyze and provide mitigation strategies for collision incidents, such as identifying common causes and patterns, enhancing sensor technologies, and implementing advanced driver assistance systems [38] [39] [40] [41] [42]. Additionally, it discusses the legal and ethical considerations, offers training and education for automated vehicle operators, and presents future directions and challenges in collision incident prevention, such as advancements in vehicle-to-vehicle communication and the integration of artificial intelligence in collision avoidance systems.

Overall, this section provides a comprehensive overview of collision incident scenarios for both Level 1 and Level 2 Automated Vehicles, along with strategies for prevention and improvement in the field.

2.6.1 IMPORTANCE OF STUDYING COLLISION INCIDENTS

Studying collision incidents is of utmost importance in the development of Level 1 and Level 2 automated vehicles [43] [44] [45] [46]. By exploring the various scenarios in which collisions can occur, researchers and engineers can understand the challenges and limitations of these technologies. This knowledge is crucial for improving the safety features and algorithms of automated vehicles.

In Level 1 vehicles, collision incident scenarios such as rear-end collisions due to inadequate braking and side collisions during lane changes need to be thoroughly examined. For Level 2 vehicles, failure to detect pedestrians in crosswalks, rear-end collisions due to sudden vehicle deceleration, collisions during overtaking maneuvers, and intersection collisions caused by conflicting signals are critical scenarios that require attention.

Analyzing and identifying common causes and patterns, enhancing sensor technologies, and implementing advanced driver assistance systems are essential strategies for mitigating collision incidents [43] [44] [45] [46]. Ultimately, this research will pave the way for creating a comprehensive regulatory framework and training programs that are necessary for the safe and effective deployment of automated vehicles.

2.6.2 COLLISION INCIDENT SCENARIOS FOR LEVEL 1 AUTOMATED VEHICLES

Collision Incident Scenarios for Level 1 Automated Vehicles consist of a few key scenarios. One scenario involves rear-end collisions caused by inadequate braking, where the vehicle fails to stop in time and hits the vehicle in front. Another scenario encompasses side collisions during lane changes, where the vehicle fails to detect a vehicle in the adjacent lane and collides with it. Lastly, there are intersection collisions caused by misjudgment, where the vehicle misjudges the distance or speed of other vehicles and enters the intersection, resulting in a collision.

These scenarios highlight the challenges faced by Level 1 Automated Vehicles in navigating complex driving situations and avoiding collisions.

2.6.2.1 REAR-END COLLISION DUE TO INADEQUATE BRAKING

Rear-end collisions due to inadequate braking are a significant concern for Level 1 and Level 2 automated vehicles [47] [48] [49] [50]. In these scenarios, vehicles might fail to brake in time to avoid colliding with the vehicle ahead, resulting in accidents. This situation can arise if the automated vehicle's braking system doesn't respond quickly enough or if there's a delay in detecting the lead vehicle's braking action.

Addressing this issue is crucial to ensure the safety and effectiveness of automated vehicles on the road. Strategies such as analyzing common causes, enhancing sensor technologies, and implementing advanced driver assistance systems (ADAS) can help prevent and mitigate rear-end collisions.

Additionally, future advancements in vehicle-to-vehicle communication and the integration of artificial intelligence in collision avoidance systems show promise in further improving the safety standards of automated vehicles.

2.6.2.2 SIDE COLLISIONS DURING LANE CHANGES

Side collisions during lane changes are a significant concern for both Level 1 and Level 2 automated vehicles [48]. These incidents often occur when a vehicle attempts to change lanes but fails to detect the presence of another vehicle in the adjacent lane. Such situations can lead to dangerous collisions, particularly at higher speeds.

Level 1 automated vehicles, with their limited automated capabilities, may struggle to accurately perceive and respond to these scenarios, heightening the risk of accidents. Meanwhile, Level 2 automated vehicles, despite being more advanced, also encounter challenges in accurately detecting and responding to side collision risks during lane changes.

Therefore, it is crucial to develop advanced sensor technologies and implement intelligent algorithms that enhance the detection and predictive capabilities of these vehicles. These enhancements aim to mitigate the occurrence of side collisions and bolster overall road safety.

2.6.2.3 INTERSECTION COLLISION CAUSED BY MISJUDGEMENT

Intersection collisions caused by misjudgment are a significant concern for both Level 1 and Level 2 automated vehicles [41] [51]. In these scenarios, the vehicle's ability to accurately assess the intentions and movements of other vehicles or pedestrians at intersections is crucial.

Misjudgment can lead to accidents such as failing to yield the right of way, misinterpreting the speed or distance of an oncoming vehicle, or misreading the intentions of pedestrians. These incidents often occur due to limitations in the vehicle's perception or decision-making capabilities.

Addressing this issue requires advancements in sensor technologies to enhance detection, as well as the implementation of advanced driver assistance systems (ADAS) that can provide real-time feedback and warnings to the driver. By improving the ability of automated vehicles to accurately perceive and respond to intersection scenarios, the risk of collision can be significantly reduced.

2.6.3 COLLISION INCIDENT SCENARIOS FOR LEVEL 2 AUTOMATED VEHICLES

2.6.3.1 FAILURE TO DETECT PEDESTRIANS IN CROSSWALKS

Failure to detect pedestrians in crosswalks is a significant issue in the context of collision incidents involving both Level 1 and Level 2 automated vehicles [39] [52] [53]. This scenario poses a serious safety concern as automated vehicles rely on their sensors and algorithms to accurately detect and respond to pedestrians to avoid collisions.

However, there are situations where these vehicles may fail to detect pedestrians in crosswalks, either due to limitations in sensor technology or misjudgments made by the automated system. To mitigate this risk, it is crucial to identify common causes and patterns of failure, enhance sensor technologies for improved pedestrian detection, and implement advanced driver assistance systems (ADAS) that provide real-time warnings or interventions to prevent collisions.

By addressing these issues, we can work towards enhancing the safety of automated vehicles and minimizing the frequency of collision incidents involving pedestrians in crosswalks.

2.6.3.2 REAR-END COLLISIONS DUE TO VEHICLE DECELERATION

Rear-end collisions due to sudden vehicle deceleration are critical scenarios to consider for both Level 1 and Level 2 automated vehicles [54] [55] [56]. In these incidents, the vehicle ahead decelerates abruptly, necessitating a quick response from the automated system to avoid a collision.

For Level 1 vehicles, which possess basic automation capabilities, the challenge lies in the system's ability to detect the sudden deceleration of the lead vehicle and initiate appropriate braking in time. Meanwhile, Level 2 vehicles, with more advanced automation, have the potential to predict deceleration and take proactive measures to avoid collisions. However, the efficacy of these vehicles still depends on the accuracy and effectiveness of their sensors and decision-making algorithms.

Consequently, improving sensor technologies and enhancing detection capabilities are crucial steps toward mitigating rear-end collisions caused by sudden vehicle deceleration for both Level 1 and Level 2 automated vehicles.

2.6.3.3 COLLISIONS DURING OVERTAKING MANUVERS

Collisions during overtaking maneuvers are a critical concern for both Level 1 and Level 2 automated vehicles [57] [58] [59]. In these scenarios, when a vehicle attempts to overtake another vehicle on the road, various risks come into play.

Factors such as insufficient distance judgment, inadequate acceleration, and failure to detect a potential collision can contribute to accidents during overtaking maneuvers. It's crucial to analyze common causes and patterns of these collisions to develop effective mitigation strategies.

This involves enhancing sensor technologies for improved detection, implementing advanced driver assistance systems, and considering legal and ethical considerations in critical situations. Additionally, training and education for automated vehicle operators are pivotal in preventing collision incidents during overtaking maneuvers.

As advancements like vehicle-to-vehicle communication and the integration of artificial intelligence shape the future of collision avoidance systems, a comprehensive regulatory framework for automated vehicle safety standards will be vital to ensuring the overall safety and reliability of automated vehicles on the road.

2.6.3.4 INTERSECTION COLLISIONS CAUSED BY CONFLICTING SIGNALS

Intersection collisions caused by conflicting signals are concerning incidents encountered by both Level 1 and Level 2 automated vehicles [60] [61] [62]. These scenarios unfold when automated vehicles face conflicting or ambiguous traffic signals at intersections, potentially leading to collisions.

Such situations can stem from malfunctioning traffic signal equipment, poor visibility, or inadequate communication between the vehicle and the traffic infrastructure. The automated vehicle might receive conflicting instructions or misinterpret signals, leading to collisions with other vehicles or pedestrians.
Mitigating this risk entails enhancing the vehicle's sensor technologies for improved signal detection and interpretation. Additionally, integrating artificial intelligence into collision avoidance systems aids vehicles in anticipating and responding appropriately to conflicting signals.

Developing a regulatory framework for automated vehicle safety standards is essential to ensure consistency in addressing this issue across the board. By tackling these challenges, collision incidents arising from conflicting signals can be effectively prevented, contributing to safer and more reliable automated transportation systems.

2.6.4 ANALYSIS AND MITIGATION STRATEGIES FOR COLLISION INCIDENTS

In the analysis and mitigation strategies for collision incidents involving both Level 1 and Level 2 automated vehicles, several key approaches are crucially employed [44] [63] [64]. Firstly, identifying common causes and patterns of collisions is paramount. This insight serves as the foundation for enhancing sensor technologies, thereby improving the detection capabilities of these vehicles.

Moreover, implementing advanced driver assistance systems (ADAS) plays a pivotal role in further mitigating collision risks by providing additional assistance and warnings to drivers. These strategies aim to address specific scenarios such as inadequate braking, misjudgments at intersections, failure to detect pedestrians, and sudden deceleration.

By comprehending these incident scenarios and implementing appropriate measures, the overall safety and effectiveness of automated vehicles can witness significant enhancements.

2.6.5 METHODS PROPOSED FOR CALCULATING COLLISION METRICS

Understanding and quantifying the factors influencing crash severity and collision types involving Automated Vehicles (AVs) stands as a pivotal pursuit in enhancing their safety and operational performance. Wang and Li (2019) [63] delve into this realm, investigating the multifaceted elements impacting crash severity and collision types within AV scenarios. Their study explores variables such as driving mode, roadway characteristics, liability factors, and the involvement of pedestrians/cyclists. Employing statistical modeling approaches, specifically ordinal logistic regression and CART classification tree analysis, the research endeavors to elucidate the interplay of these factors and their influence on crash outcomes. The study posits that the outcomes gleaned from these statistical methods offer insights crucial for assessing and subsequently enhancing the safety performance of Automated Vehicles.

Additionally, Wishart et al. (2020) [13] contribute to this domain by proposing a metric termed Collision Incident (CI), elucidating instances where the ego vehicle is deemed at fault in a collision. This metric is formulated as a frequency measure using binary variables (1 denoting a collision occurrence and 0 indicating the absence of a collision). Wishart et al.'s framework for CI determination relies on comprehensive data examination, including insights from on-board and off-board sensors, potentially integrating vehicle event data recorder (EDR) information, along with scrutiny of police reports. Severity assessment within the CI metric employs the KABCO scale, ensuring a nuanced understanding of the collision severity.

$$CI = \begin{cases} 1 & if\ d^{lat} = 0 \wedge d^{long} = 0 \\ 0 & else \end{cases}$$

These approaches and metrics, proposed by Wang and Li (2019) [63] and Wishart et al. (2020) [13], respectively, contribute significantly to the landscape of assessing and quantifying collision incidents involving Automated Vehicles. Their methodologies, spanning statistical modeling and frequency-based metric formulation, offer avenues for comprehensively understanding crash scenarios and gauging safety performance, thereby advancing the ongoing pursuit of ensuring safer AV operations.

2.6.6 FUTURE DIRECTIONS AND CHALLENGES IN COLLISION INCIDENT PREVENTION

2.6.6.1 ADVANCEMENTS IN VEHICLE-TO-VEHICLE COMMUNICATION

Advancements in Vehicle-to-Vehicle (V2V) Communication have emerged as pivotal tools in preventing collision incidents for both Level 1 and Level 2 Automated Vehicles [65] [66]. This technology facilitates direct communication between vehicles, enabling the exchange of crucial information encompassing position, speed, and direction in real-time.

By sharing such data, vehicles can proactively anticipate potential collisions and take preemptive actions to avoid them. Moreover, V2V Communication enables cooperative maneuvers, like coordinated lane changes, significantly enhancing road safety. Additionally, this technology empowers vehicles to receive warnings and alerts from both other vehicles and infrastructure, providing vital information about potential hazards or dangerous scenarios.

Overall, the evolution of V2V Communication contributes significantly to the development and deployment of robust collision avoidance systems, fostering the safety and efficiency of automated vehicles on the road.

2.6.6.2 INTEGRATION OF ARTIFICIAL INTELLIGENCE IN COLLISION AVOIDANCE SYSTEMS

The integration of artificial intelligence (AI) in collision avoidance systems stands as a pivotal factor in bolstering the safety measures for both Level 1 and Level 2 automated vehicles [55] [60]. AI plays a significant role in the detection of potential collision incidents and the swift decision-making needed to evade them. In Level 1 vehicles, where automation capabilities are limited, AI algorithms are instrumental in identifying scenarios like rear-end collisions due to inadequate braking and side collisions during lane changes [55]. For Level 2 vehicles, which possess more advanced automation, AI algorithms are critical in detecting pedestrians in crosswalks, averting rear-end collisions stemming from sudden vehicle deceleration, preventing collisions during overtaking maneuvers, and addressing intersection collisions caused by conflicting signals [60].

The integration of AI within collision avoidance systems aims to optimize the safety of automated vehicles by enabling rapid and precise decision-making in critical situations.

2.6.6.3 REGULATORY FRAMEWORK FOR AUTOMATED VEHICLE SAFETY STANDARDS

The regulatory framework [67] plays a vital role in ensuring the safety of both level 1 and level 2 automated vehicles. It is imperative to establish comprehensive regulations that specifically focus on the unique collision scenarios associated with these vehicles [68]. These regulations should provide clear guidelines and standards to address common causes and patterns of collisions. Furthermore, it is crucial to enhance sensor technologies to improve collision detection and implement advanced driver assistance systems (ADAS) [69].

In addition to technical considerations, it is essential to address the legal and ethical aspects of collision incidents involving automated vehicles [67]. Manufacturers and operators need to be aware of potential liability issues that may arise. To handle critical situations, it is necessary to develop ethical decision-making algorithms [68].

Moreover, training and education for operators of automated vehicles are of utmost importance [67]. Operators should be well-versed in collision scenarios and safe driving practices. Additionally, emergency response training should be provided to ensure effective handling of unforeseen situations.
Looking towards the future, preventing collision incidents will require advancements in vehicle-to-vehicle communication [70]. This will allow vehicles to share critical information, thereby improving collision avoidance systems. Furthermore, the integration of artificial intelligence into collision avoidance systems is expected to play a significant role in enhancing safety [70].

Overall, establishing a robust regulatory framework, addressing legal and ethical considerations, providing comprehensive training, and integrating technological advancements are crucial elements in preventing collision incidents involving automated vehicles.

2.7 OEDR AND OEDR RESPONSE TIME

The detection and response capabilities in Level 1 and Level 2 automated vehicles, referred to as Object and Event Detection and Response (OEDR), present significant challenges. Understanding the limitations of OEDR and response time is crucial for effective system functioning. OEDR is the system's ability to identify and respond to objects and events in the surrounding environment, while response time determines the speed at which potential hazards can be detected and reacted to.

Various factors impact OEDR response time, including sensor accuracy and reliability, processing speed of automated systems, and environmental conditions and obstacles. Limited response time can result in delayed detection and recognition of objects, increasing the risk of collisions and accidents. It also makes navigating complex traffic situations a challenge for Level 1 automated vehicles [54]. In Level 2 vehicles, striking a balance between driver assistance and human intervention becomes crucial to prevent misinterpretation of situations. Additionally, ensuring smooth transitions between automated and manual control poses another challenge.

Efforts are being made to improve OEDR response time through advancements in sensor technology, faster and more efficient processing, and incorporating artificial intelligence and machine learning techniques [71]. Regulatory considerations, such as evaluating safety requirements and exploring potential frameworks for future developments, are also important [72]. Future research in OEDR response time focuses on exploring next-generation sensor technologies, enhancing real-time data processing capabilities, and fostering collaboration between industry and research institutions [73].

2.7.1 FACTORS AFFECTING OEDR RESPONSE TIME

2.7.1.1 SENSOR ACCURACY AND RELIABILITY

Sensor accuracy and reliability significantly influence the Object and Event Detection and Response (OEDR) in both level 1 and level 2 automated vehicles. These vehicles rely on sensors to accurately perceive and interpret their surroundings for safe and effective operation. However, ensuring the precision and dependability of these sensors presents challenges. Factors like sensor calibration, fusion techniques, and environmental conditions impact sensor accuracy and reliability. Strategies to address these challenges involve improving sensor technology and calibration methods. These improvements can enhance OEDR response time, bolstering vehicle safety.

Advancements in sensor technology, the integration of artificial intelligence and machine learning, and improved real-time data processing capabilities all contribute to enhancing OEDR response time. Collaborations between industry and research institutions drive further innovations in sensor technologies, ultimately boosting the effectiveness of OEDR systems in automated vehicles [60]. Research on machine-learning solutions is particularly relevant in addressing faults in sensor systems, ensuring reliability in the Industry 4.0 era [74]. Information fusion from multiple sensors using machine learning techniques has also shown promise in various applications, including human activity recognition [75]. These collective efforts advance the capabilities and reliability of sensors critical for OEDR in automated vehicles.

2.7.1.2 PREPROCESSING SPEED

The speed at which Level 1 and Level 2 automated vehicles process information is a critical factor impacting their overall operation. Challenges surrounding processing speed exist within these vehicles' automated systems, presenting obstacles to their effective functioning [76].

The necessity for highly accurate and reliable sensors is a primary challenge affecting processing speed. These sensors must provide precise data for the automated systems to operate effectively. Moreover, environmental conditions and obstacles can impede the speed at which these systems process information, potentially leading to delays in object detection and recognition [77]. Such delays elevate the risk of accidents and collisions.

Navigating complex traffic situations further compounds these challenges. Limited processing speed poses difficulties in maneuvering through intricate scenarios [78]. Achieving the right balance between driver assistance and human intervention, avoiding misinterpretation of situations, and ensuring smooth transitions between automated and manual control are significant challenges for Level 2 automated vehicles [79].

Improving processing speed involves several strategies [80]. Advancements in sensor technology can enhance sensor accuracy and reliability, critical for the efficient functioning of these vehicles. Increasing processing efficiency and integrating artificial intelligence and machine learning are avenues to explore, optimizing processing speeds and enhancing overall performance [81].

Beyond technological aspects, regulatory considerations come into play concerning limited processing speed [72]. This includes adhering to existing standards and guidelines while ensuring that Level 1 and Level 2 vehicles meet safety requirements [82]. Developing frameworks for future advancements in this domain is crucial.

Future research will focus on exploring next-generation sensor technologies and enhancing real-time data processing capabilities [72]. Collaborative efforts between industry and research institutions will be pivotal in driving advancements in processing speed and overall vehicle performance [72].

In summary, processing speed is a fundamental element influencing the operation of Level 1 and Level 2 automated vehicles. Addressing challenges related to limited processing speed, implementing strategies to enhance it, and considering regulatory aspects will contribute to the future development and improvement of these vehicles.

2.7.1.3 ENVIRONMENTAL CONDITIONS AND OBSTICLES

Environmental conditions and obstacles significantly impact Object and Event Detection and Response (OEDR) and its response time in both level 1 and level 2 automated vehicles [83]. These factors encompass various external conditions, including weather conditions, road conditions, and the presence of obstacles. Environmental conditions like heavy rain, fog, or snow can severely reduce sensor visibility and accuracy, leading to delayed object detection and recognition [83]. Moreover, obstacles such as road debris or sudden constructions pose challenges for safe navigation by automated vehicles [85].

Robust algorithms and systems are essential to effectively handle such conditions and obstacles, ensuring the safety of vehicle occupants and other road users [84]. Advances in sensor technology, processing speed, and the integration of artificial intelligence and machine learning contribute to improving OEDR response time [84]. These advancements enable automated vehicles to efficiently navigate various environmental conditions and obstacles, enhancing safety measures.

Regulatory considerations and collaborations between industry and research institutions are crucial to establishing safety standards and evaluating requirements for level 1 and level 2 vehicles [86]. Such collaborations facilitate the development and implementation of effective strategies to overcome environmental challenges and ensure safer automated driving.

Future research in OEDR response time focuses on exploring next-generation sensor technologies, enhancing real-time data processing capabilities, and fostering collaborative efforts to drive advancements in handling environmental conditions and obstacles [87].

2.7.2 METHODS PROPOSED FOR CALCULATING OEDR METRICS

The Object and Event Detection and Response (OEDR) response time represents a fundamental metric in evaluating the safety performance of automated vehicles, specifically concerning how swiftly the vehicle's system detects and reacts to objects or events within its environment (NHTSA; UNECE, 2022). This critical metric is calculated based on the temporal difference between the initial detection of an object or event by the vehicle's array of sensors and the subsequent initiation of an appropriate response, such as steering adjustments or braking maneuvers.

In practical terms, the OEDR response time is computed as the duration between the moment an object or event is first identified by the vehicle's sensory apparatus and the instant when the automated system triggers a suitable reaction to address the detected hazard. This interval delineates the efficiency and effectiveness of the vehicle's response mechanism in navigating its surroundings and mitigating potential collision risks.

The significance of the OEDR response time lies in its pivotal role in ensuring the safety and reliability of automated vehicles (NHTSA; UNECE, 2022). A swift and accurate response to detected objects or events is imperative to prevent collisions and maintain safe driving conditions. A shorter OEDR response time signifies a more efficient and proactive automated system capable of promptly identifying hazards and taking appropriate corrective actions to avert potential collisions, thereby enhancing overall road safety.

2.8 BEHAVIOUR OF AUTOMATED VEHICLES INSIDE AND OUTSIDE OF OPERATIONAL DESIGN DOMAIN (ODD)

2.8.1 INSIDE ODD

Performance Inside Operational Design Domain (ODD) refers to the comprehensive evaluation and analysis of the operational capabilities of Level 1 and Level 2 automated vehicles operating within their predefined operational boundaries [43] [88] [89]; Marcano et al., 2020). This encompasses the meticulous examination of these vehicles' adherence to traffic rules and regulations [69], as well as their behavior in a wide range of complex and dynamic weather and road conditions [89].

By precisely scrutinizing these critical factors, profound insights can be gained and extensive understanding into the vehicles' exceptional ability to consistently and reliably operate in a safe, efficient, and effective manner within their designated ODD can be established [88]. In addition, the evaluation process includes a meticulous assessment of the vehicles' flawless compliance with traffic regulations, thereby ensuring utmost safety not only for the occupants of the automated vehicles but also for all other road users [69].

Moreover, an in-depth comprehension of how these automated vehicles adeptly handle diverse and unpredictable weather and road conditions plays an irreplaceable and indispensable role in evaluating their performance reliability, robustness, and adaptability within their operational boundaries [89] [90].

2.8.1.1 EVALUATION OF VEHICLE BEHAVIOUR WITHIN PREDEFINED OPERATIONAL BOUNDARIES

Assessing the performance of Level 1 and Level 2 automated vehicles heavily relies on evaluating how these vehicles behave within their predefined operational boundaries [91] [94] [92] [93]. This evaluation encompasses examining the vehicle's capacity to function within its designated operational parameters while adhering to traffic rules and regulations [91]. Moreover, it necessitates testing these vehicles in diverse weather and road conditions to ascertain their adaptability and reliability, especially in adverse situations [94].

Understanding how these vehicles respond to unexpected circumstances and their ability to interact with both non-automated vehicles and pedestrians is pivotal in gaining a comprehensive insight into their performance, both within and outside the Operational Design Domain (ODD) [92]. These evaluations serve a crucial role in pinpointing any challenges or limitations in the vehicle's performance and contribute significantly to shaping future enhancements. Advancements in AI, machine learning algorithms, sensor technologies, and collaboration among stakeholders are key aspects that could be influenced by these evaluations [93].

2.8.2 OUTSIDE ODD

Performance Outside Operational Design Domain (ODD) is a critical aspect that needs to be thoroughly evaluated when examining the performance of Level 1 and Level 2 automated vehicles [95] [92] [96] [97]. This evaluation encompasses an in-depth assessment of how these vehicles respond in unexpected situations, their adaptability to diverse road infrastructure and signage, as well as their interaction with non-automated vehicles and pedestrians [95].

By comprehensively understanding how these vehicles perform outside their predefined operational boundaries, we can gather invaluable insights into their capabilities, limitations, and potential areas for enhancement [92]. Moreover, this meticulous evaluation process aids in identifying areas that necessitate improvement and effectively highlights the pressing challenges that demand immediate attention, such as the vehicle's immediate response to unexpected events and its seamless ability to navigate through complex traffic scenarios [97].

Ensuring optimal performance outside ODD is undoubtedly a pivotal factor in elevating the overall safety and efficiency of automated vehicles on public roads, ultimately contributing to a future where transportation is more reliable, secure, and innovative.

2.8.2.1 ASSESSMENT OF VEHICLE RESPONSE IN UNEXPECTED SITUATIONS

The assessment of vehicle response in unexpected situations is a critical aspect of evaluating the performance of Level 1 and Level 2 automated vehicles [92] [69] [99] [98]. It involves analyzing how these vehicles react and adapt when confronted with unforeseen events or hazards on the road. Factors such as the speed and accuracy of the vehicle's response, its ability to detect and avoid potential collisions, and its capacity to handle unexpected traffic scenarios need to be carefully examined [69].

Additionally, the adaptability of the vehicle to diverse road infrastructure and signage, as well as its interaction with non-automated vehicles and pedestrians, play a significant role in performance evaluation [99] [98]. Understanding how these automated vehicles perform in unexpected situations is essential for improving their safety and effectiveness on the road.

2.8.3 MANAGING OPERATIONAL DESIGN DOMAIN (ODD) FOR AUTOMATED VEHICLES

The operational deployment of Automated Vehicles (AVs) is governed by the concept of the Operational Design Domain (ODD), a delineation of conditions within which an AV is intended to operate safely [100]. The absence of a standardized evaluation process for determining an AV's ODD poses challenges in ensuring their safe and appropriate use. This gap is recognized within the framework of SAE levels of automation, emphasizing the critical need to define and assess ODD for AV systems.

The study by Hong (2020) [100] investigated a risk-based approach to delineate the ODD, introducing a framework that assesses an automation system's reliability concerning its intended functions [100]. This risk-based framework involves an evaluation of potential unreliable behaviors of the automation system, accompanied by a preliminary hazard analysis to identify resulting hazards. It considers the impact of external conditions on both the system's reliability and the consequences of unreliable behavior. Utilizing a traditional risk matrix, this approach transforms an acceptable level of risk into an acceptable volume within the ODD hyperspace, collectively defining the overall system ODD as the union of these acceptable volumes.

Furthermore, once the ODD is defined, effective ODD management is crucial to prevent the utilization of automation beyond its designated domain [100]. ODD management involves the observation and assessment of prevailing conditions, ensuring compliance with the predetermined ODD. Depending on the SAE automation level, this role may be executed automatically by the system or by human operators. The study examines recent accidents involving failures of driving automation systems to operate within their intended ODD. It identifies potential failure modes in human ODD management, including perception, comprehension, and projection failures, emphasizing the importance of enhancing driver-automation interfaces and training to support improved ODD management.

In summary, this investigation underscores the significance of delineating and managing the Operational Design Domain for Automated Vehicles [100]. The risk-based approach introduced provides a methodical means to assess and define the ODD, while insights into failure modes in ODD management highlight the need for enhanced human-automation interactions to ensure AVs operate within their intended domain, minimizing risks associated with their use beyond the ODD.

3 HMI METRICS

Human Machine Interaction (HMI) plays a crucial role in level 1 and level 2 automated vehicles. It is important to understand the significance of HMI in these automation levels to ensure effective and safe interactions between humans and machines. Evaluating HMI performance through the use of metrics is essential in assessing system effectiveness [8] [101].

By tracking driver engagement and attention, evaluating driver alerts and warnings, and assessing driver response time and reaction to system requests, HMI metrics provide valuable insights into the performance of level 1 automated vehicles [102] [8]. Similarly, in level 2 automation, monitoring driver readiness to take over control, measuring driver workload and cognitive demand, and assessing driver situational awareness and understanding of system limitations are important metrics to consider [8].

However, there are also challenges and limitations that need to be addressed, such as potential distractions and complacency, compatibility with diverse driver populations, and limitations of current HMI technologies [11] [8]. Looking towards the future, advancements in HMI technologies for higher automation levels, integration of artificial intelligence and machine learning in HMI design, and the potential impact of HMI on the acceptance and adoption of automated vehicles are areas that hold promise [8] [103].

3.1 OVERVIEW OF HMI METRICS IN AUTOMATED VEHICLES

HMI plays a crucial role in providing an effective interface between humans and automated vehicles. In the context of Level 1 and Level 2 automation, HMI serves as the primary means of communication and collaboration between the driver and the vehicle. The design of HMI must prioritize user-centered principles, integrating visual and auditory cues to ensure intuitive and easy-to-use interfaces [103] [104] [8].

Metrics for Level 1 automation focus on tracking driver engagement, evaluating the effectiveness of alerts and warnings, and assessing driver response time [8]. For Level 2 automation, metrics shift to monitoring driver readiness to take over control, measuring driver workload and cognitive demand, and assessing driver situational awareness [8].

3.2 IMPORTANCE OF HMI METRICS IN LEVEL 1 AND LEVEL 2 AUTOMATION

The importance of Human Machine Interaction (HMI) in Level 1 and Level 2 automation is crucial for the effective functioning of automated vehicles. HMI plays a significant role in facilitating communication and collaboration between humans and machines, ensuring seamless interaction and control [102] [105]. It enables drivers to understand and interpret the system's feedback, alerts, and warnings, thereby improving their overall situational awareness and decision-making. Moreover, HMI metrics serve as valuable tools for evaluating the performance of automated systems, allowing for the identification of potential areas of improvement [103] [105]. By tracking driver engagement, assessing response time, and measuring workload and cognitive demand, HMI metrics provide valuable insights into the effectiveness and efficiency of automated systems [103] [105].

As the field of automation continues to evolve, advancements in HMI technologies, integration of artificial intelligence, and consideration of diverse driver populations will further enhance the role and impact of HMI in automated vehicles [103].

HMI metrics play a significant role in evaluating the performance of automated vehicle systems at Level 1 and Level 2 automation [102] [105]. These metrics provide valuable insights into the effectiveness of the human-machine interaction, helping designers and engineers assess the overall system performance [105] [10]. In Level 1 automation, HMI metrics focus on tracking driver engagement and attention, evaluating the effectiveness of driver alerts and warnings, and assessing driver response time and reaction to system requests [102] [105]. At Level 2 automation, HMI metrics shift to monitoring driver readiness to take over control, measuring driver workload and cognitive demand, and assessing driver situational awareness and understanding of system limitations [102] [105]. By analyzing these metrics, researchers can address challenges and limitations, such as potential distractions and complacency, compatibility with diverse driver populations, and the limitations of current HMI technologies.

Looking ahead, advancements in HMI technologies for higher automation levels, the integration of artificial intelligence and machine learning in HMI design, and the potential impact of HMI on the acceptance and adoption of automated vehicles are promising future directions.

3.3 MENTAL MODELS

Mental models play a crucial role in the operation of both Level 1 and Level 2 automated vehicles. These models serve as the cognitive representations that drivers and users build to understand and interact with the vehicle's capabilities and behavior. In Level 1 automation, which provides basic assistance to the driver, mental models help users comprehend the system's limitations and functions [106] [107]. They also aid in interpreting the information provided by the vehicle and making informed decisions while driving [106] [107].

In Level 2 automation, mental models become even more significant as they enable users to understand the vehicle's advanced capabilities, such as partial self-driving features [106] [108]. They support drivers in effectively interacting with the vehicle and transitioning between automated and manual driving modes [106] [108]. Although mental models provide several advantages, such as enhanced user experience and safety, they also come with challenges [108] [107]. These challenges include designing user-friendly interfaces, ensuring user acceptance of the technology, and addressing ethical and legal implications [106] [108].

Future research and development are necessary to improve mental models and address these challenges, as well as explore potential enhancements and innovations in the field [106] [108].

3.3.1 DEFINITIONS AND EXPLANATION OF MENTAL MODELS

Mental models are cognitive representations that individuals use to understand and predict the behavior of complex systems, such as automated vehicles. These mental models play a crucial role in Level 1 and Level 2 automation by shaping how drivers interact with and trust these vehicles [106] [109] [88]. Fig.1 [107] illustrates how the driver's mental model depends on the preliminary system description and driving experience.

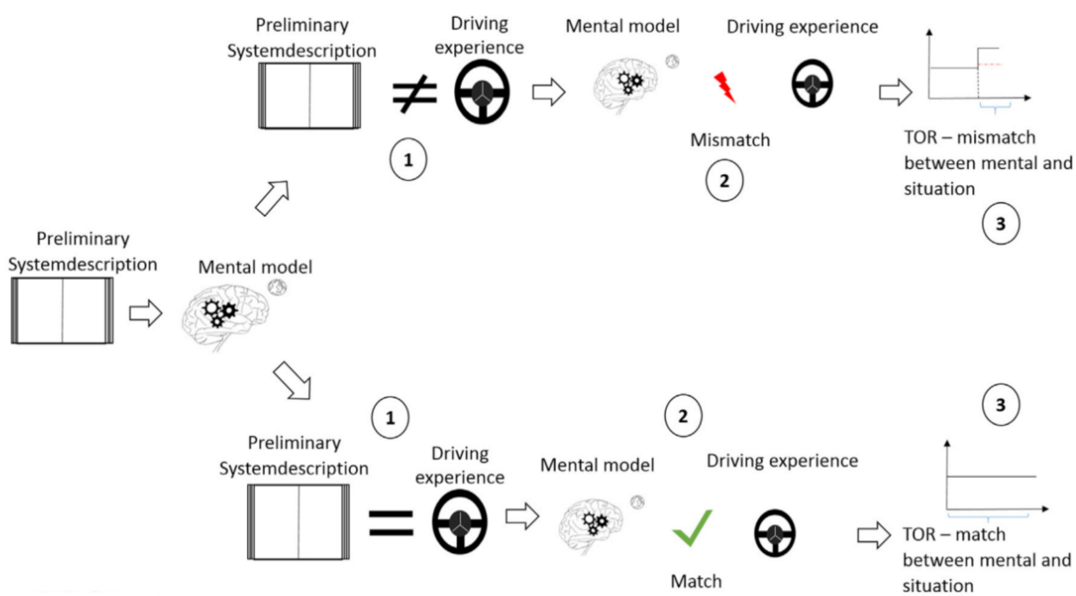

Figure 1:Driver's mental model based on preliminary system description [107]

In Level 1 automation, which involves driver assistance features such as adaptive cruise control, mental models are utilized to understand the capabilities and limitations of the system. By forming a mental model of the automated features, drivers can effectively cooperate with the technology and intervene when necessary [106]. However, there are also limitations to mental models in Level 1 automation, as drivers can become overly reliant on the system and may struggle to regain control in critical situations [106].

In Level 2 automation, which allows for hands-off driving under specific conditions, mental models are more complex and dynamic [106] [109]. Drivers must understand how the system operates in various driving scenarios and anticipate its behavior [106] [109]. This requires a higher level of trust and a well-developed mental model [109]. However, challenges arise with Level 2 automation, such as complacency and the potential for drivers to disengage from the driving task [106] [109].
Understanding the similarities and differences in mental models between Level 1 and Level 2 automation is essential for improving user experience and ensuring safety [106] [109] [88]. Future research and developments in mental models for automated vehicles should focus on enhancing the accuracy and efficiency of these mental representations [110] [111]. However, there are also technical, human factors, and ethical challenges that need to be considered when implementing mental models in automated vehicles [110] [109] [88].

Overall, mental models play a significant role in shaping the interaction between drivers and automation, and their continued study is essential for advancing the field of automated vehicles.

3.3.2 LEVEL 1 AUTOMATED VEHICLES AND THEIR MENTAL MOELS

Level 1 automated vehicles refer to vehicles that can perform specific automated functions but the human is still responsible. In these vehicles, mental models play a crucial role in ensuring effective human-automation interaction [106] [110].

One of the main mental models utilized in Level 1 automated vehicles is the understanding of the vehicle's capabilities and limitations. Users need to have a clear mental model of what the automated system can and cannot do, to avoid potential risks and effectively supervise the vehicle's actions [106].

Additionally, mental models are essential in understanding the vehicle's behavior during automated functions. Users need to develop a mental model of how the system navigates, accelerates, brakes, and interacts with other road users [106]. This understanding allows them to predict and anticipate the vehicle's actions, ensuring a safer and more efficient driving experience [106].

However, it is important to recognize the limitations of mental models in Level 1 automated vehicles [106] [110]. Users may over-rely on the system or become complacent, assuming the vehicle can handle all situations [106] [110]. This can lead to a lack of vigilance and slower response times when intervention is required [106] [110].

In summary, mental models play a significant role in Level 1 automated vehicles by helping users comprehend the system's capabilities and behaviors [106]. They contribute to ensuring effective human supervision and enhancing safety during automated functions [106]. However, users must also be aware of the limitations of mental models and the importance of remaining actively engaged in the driving task [106] [110].

3.3.3 LEVEL 2 AUTOMATED VEHICLES AND THEIR MENTAL MOELS

Level 2 automated vehicles denote vehicles with a higher level of automation compared to Level 1 vehicles [106] [107] [112]. In Level 2 automation, drivers can delegate certain driving tasks to the vehicle, enabling reduced involvement in the driving process while maintaining necessary situational awareness and readiness to resume control when required [106] [112].

In this scenario, drivers' mental models play a pivotal role [106] [107]. These mental models encompass internal representations and understanding regarding the vehicle's operations, capabilities, and limitations [106] [107].

The utilization of mental models in Level 2 automation empowers drivers to interact effectively with the vehicle and make informed decisions [106]. A clear mental model of the automation system assists drivers in anticipating the vehicle's behavior and determining when intervention is necessary, contributing to improved safety and user experience [106].

Nevertheless, challenges associated with mental models in Level 2 automation exist [106] [107]. Drivers might form incorrect or incomplete mental models, potentially leading to confusion and unsafe situations. Ensuring accurate mental models among drivers requires adequate training and education [106] [107]. Additionally, the automated system's design should provide clear and consistent feedback to aid drivers in developing and updating their mental models [106] [107].

Understanding the significance of mental models in Level 2 automated vehicles is crucial for successful technology implementation and use [106] [112]. By considering the role of mental models, designers and researchers can strive towards enhancing user experience, optimizing safety, and addressing challenges associated with automated driving [106] [112].

3.3.4 SIGNIFICANCE OF DRIVER'S MENTAL MODELS IN AUTOMATED VEHICLES

Driver's mental models play a significant role in both Level 1 and Level 2 automated vehicles. Understanding the driver's perception and expectations becomes crucial in Level 1 automation to align their mental model with automation capabilities [112]. In Level 2 automation, the complexity of driver-automation interaction accentuates the impact of the driver's mental model on decision-making [113].

Evaluating and enhancing these mental models holds the potential to foster improved trust and acceptance of automation, thereby enhancing safety and performance [114] [115]. Moreover, designing effective human-machine interfaces based on these mental models becomes essential [114].

Studying driver's mental models can be accomplished through various methods such as surveys, interviews, observations, and cognitive modeling techniques [113]. However, challenges like individual mental model variability and ethical considerations need addressing [113].

Case studies on driver's mental models provide valuable insights for future research directions, including exploring advanced automation levels, conducting longitudinal studies, and incorporating these mental models into automation design and development [112] [115]. Considering driver's mental models in automated vehicles is crucial, and future implications and directions remain areas for further exploration [112] [114].

3.3.5 METHODS TO STUDY DRIVER'S MENTAL MODELS

3.3.5.1 SURVEYS AND QUESTIONNAIRS

Surveys and questionnaires serve as commonly used methods for studying driver's mental models in the context of Level 1 and Level 2 automated vehicles. These tools enable researchers to collect both quantitative and qualitative data regarding the driver's perceptions, expectations, and understanding of automation [116] [117].

Surveys provide a systematic and efficient way to collect data from a large number of participants. On the other hand, questionnaires allow for a more in-depth exploration of specific aspects related to driver mental models [118] [119].

Through analysis of the collected responses, researchers can gain insights into the factors influencing driver mental models and pinpoint challenges in aligning these mental models with automation capabilities. The information derived from surveys and questionnaires significantly enhances our understanding of driver mental models, facilitating the design of effective human-machine interfaces and contributing to improved safety in the implementation of automated vehicles [116] [117].

3.3.5.2 INTERVIEWS AND OBSERVATIONS

Interviews and observations are important methods for studying driver's mental models in Level 1 and Level 2 automated vehicles. These methods allow researchers to directly gather insights and data from drivers themselves, providing valuable information on their perceptions, expectations, and decision-making processes.

By conducting interviews, researchers can gain a deeper understanding of the factors that influence drivers' mental models and the challenges they face in aligning these models with automation capabilities.

Observations, on the other hand, allow researchers to directly observe and analyze the complex interaction between drivers and automation in Level 2 vehicles. These methods can provide valuable insights for enhancing trust and acceptance of automation, improving safety and performance, and designing effective human-machine interfaces in automated vehicles.

However, there are challenges and limitations to consider, such as the variability in individual mental models, ethical considerations in data collection, and the validity and reliability of measurement techniques. Nonetheless, through careful study and analysis, researchers can uncover key findings and implications that can inform future research and the design and development of automated vehicles.

3.3.5.3 COGNITIVE MODELING TECHNIQUES

Cognitive modeling techniques offer insights into drivers' perceptions, expectations, and decision-making processes. By studying these mental models, researchers aim to enhance trust and acceptance of automation, improve safety and performance, and design effective human-machine interfaces [106] [108].

Various methods, including surveys, questionnaires, interviews, observations, and cognitive modeling techniques, can be employed to study these mental models. However, researchers must address challenges and limitations in their research, such as individual variability, ethical considerations, and measurement validity and reliability [107] [108] [106].

Ultimately, insights gained from case studies and future research can significantly inform the design and development of automated vehicles by incorporating driver's mental model.

3.3.6 INCORPORATING DRIVER’S MENTAL MODELS IN AUTOMATION DESIGN AND DEVELOPMENT

Incorporating driver's mental models in automation design and development is a crucial aspect of ensuring the effective integration of Level 1 and Level 2 automated vehicles. By understanding the cognitive processes, perceptions, and expectations of drivers, automation systems can be designed to align with the driver's mental model. This alignment is essential for enhancing trust and acceptance of automation, improving safety and performance, and designing effective human-machine interfaces.

To study driver's mental models, various methods can be utilized, such as surveys, questionnaires, interviews, observations, and cognitive modeling techniques. However, there are challenges and limitations in studying driver's mental models, including the variability in individual mental models, ethical considerations in data collection, and the validity and reliability of measurement techniques.
By addressing these challenges and conducting further research, we can achieve a deeper understanding of driver's mental models and their significance in automated vehicles.

3.3.7 FUTURE DIRECTIONS AND IMPLEMENTATIONS

Future directions in driver's mental models research include investigating the impact of these models on driver behavior and performance in Level 1 and Level 2 automated vehicles. This could involve studying how mental models influence trust and acceptance of automation, as well as decision-making processes. Additionally, there is a need to explore effective ways of designing human-machine interfaces that align with driver mental models. Future research should also focus on developing longitudinal studies to understand how driver mental models evolve over time as automation technology advances. Lastly, there is a call for incorporating driver mental models into the design and development of automated vehicles to enhance safety and performance.

3.4 TRUST

Driver's trust in Level 1 and Level 2 automated vehicles is a crucial aspect of the widespread adoption and successful implementation of these technologies [120]. It is important to understand the factors that influence driver's trust in order to address any concerns or barriers that may exist. Factors such as the reliability of automated systems, transparency in system operation, driver's understanding of automation capabilities, perception of system limitations, and trust in manufacturers and regulatory bodies all play a significant role in shaping trust levels [88] [121] [122]. Moreover, the impact of trust on driver behavior, including compliance with automated systems, driver engagement and vigilance, acceptance of system recommendations, and willingness to relinquish control to automation, further underscores the importance of building and maintaining trust [122] [120].

However, there are several challenges in building trust, including the lack of standardization in automated systems, the need for effective communication and education about automation, addressing concerns about system failures and malfunctions, overcoming skepticism and fear of technology, and building trust over time through positive experiences [88] [121] [122].

To enhance driver's trust, strategies such as improving system reliability and performance, enhancing transparency in system decision-making, providing clear and accurate information to drivers, offering comprehensive training and education programs, and establishing industry-wide safety standards and regulations can be employed [88] [121] [122]. Additionally, case studies analyzing driver trust in Level 1 and Level 2 automation, as well as their impact on driver behavior and strategies to enhance trust, can provide valuable insights for the future of automated vehicles and inform recommendations for building and maintaining driver's trust [120].

3.4.1 FACTORS INFLUENCING DRIVER'S TRUST

Factors influencing driver's trust in Level 1 and Level 2 automated vehicles play a crucial role in the acceptance and successful integration of these technologies. The reliability of automated systems is one such factor, as drivers need assurance that these systems will perform consistently and accurately [123]. The transparency of system operation also influences trust, with drivers requiring a clear understanding of how the automation works and makes decisions [109]. Furthermore, the driver's understanding of the capabilities and limitations of automation affects trust, as does their perception of the trustworthiness of manufacturers and regulatory bodies [124]. Addressing these factors is vital for building and maintaining driver's trust in Level 1 and Level 2 automated vehicles [124].

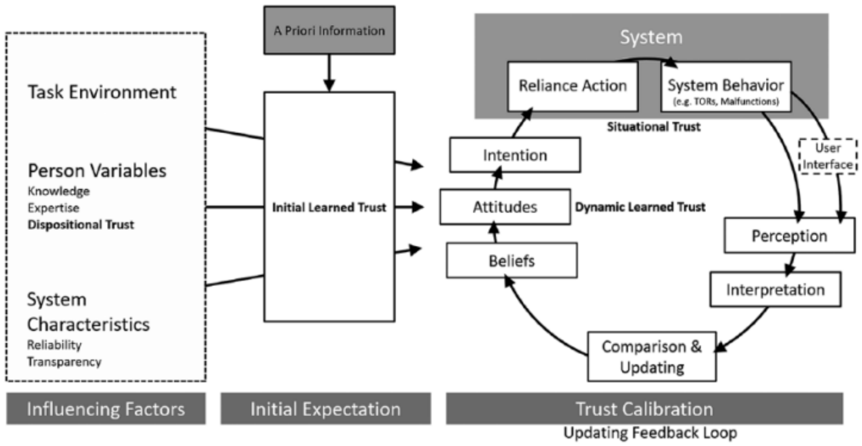

Figure 2: Factors influencing Trust [109]

3.4.1.1 RELIABILITY OF AUTOMATED SYSTEMS

Reliability of automated systems is a crucial factor in determining driver's trust in Level 1 and Level 2 automated vehicles [123]. Drivers need to feel confident that the automated systems will function consistently and accurately without any glitches or malfunctions [124]. Reliability is directly linked to the performance of the automated systems, as any errors or failures can undermine the trust that drivers have in the technology [109]. Factors such as system responsiveness, accuracy in detecting and responding to the environment, and the ability to handle various driving scenarios play a significant role in establishing reliability [19]. Manufacturers and developers must prioritize enhancing the reliability of automated systems through rigorous testing, continuous improvement, and adherence to industry-wide safety standards [19]. By ensuring that the technology consistently performs as expected, trust in Level 1 and Level 2 automated vehicles can be fostered, leading to increased acceptance and adoption of these technologies by drivers.

3.4.1.2 TRANSPARENCY OF SYSTEM OPERATION

Transparency of system operation is a crucial factor influencing driver's trust in Level 1 and Level 2 automated vehicles. When drivers are able to understand how these systems operate, they are more likely to trust and rely on them [109]. Transparency provides drivers with a clear understanding of how the automated system makes decisions, which allows for better predictability and promotes a sense of control [120]. Clear visibility into the system's decision-making process can also help drivers identify and correct any potential errors or biases [109]. Additionally, transparency can contribute to the driver's confidence in the system's capabilities, leading to a higher level of trust [125]. Providing drivers with comprehensive information about the system's operation, limitations, and potential risks can foster transparency and enhance driver trust in Level 1 and Level 2 automated vehicles.

3.4.1.3 DRIVER’S UNDERSTANDING OF AUTOMATION CAPABILITIES

Driver's understanding of automation capabilities is a crucial factor in determining their trust in Level 1 and Level 2 automated vehicles [120]. The level of trust a driver has in the technology depends on their comprehension of what the automation system is capable of and how it functions [109]. If drivers have a clear understanding of the capabilities and limitations of the automated system, they are more likely to trust it [126]. However, if there is a lack of understanding or awareness, it can lead to skepticism and reluctance to rely on the automation features [127]. Therefore, it is essential to provide clear and accurate information to drivers about the capabilities and operation of the automation system in order to enhance their understanding and trust [109]. Additionally, improving transparency in system decision-making and offering comprehensive training and education programs can further contribute to building the driver's trust in Level 1 and Level 2 automated vehicles.

3.4.1.4 PERCEPTION OF SYSTEM LIMITATIONS

Perception of system limitations is a crucial factor in determining driver trust in Level 1 and Level 2 automated vehicles [109]. Drivers need a clear understanding of the limitations of the automated system to feel confident in its operation [88]. When drivers are aware of the system's capabilities and its boundaries, they are more likely to trust it [128]. On the other hand, a lack of transparency regarding the limitations can lead to skepticism and reduced trust [19]. Therefore, it is essential for manufacturers and regulatory bodies to provide clear and accurate information to drivers about the system's limitations. By addressing this factor, the industry can build trust and increase acceptance of Level 1 and Level 2 automated vehicles.

3.4.1.5 TRUST IN MANUFACTURERS AND REGULATORY BODIES

Trust in manufacturers and regulatory bodies is a crucial factor in shaping driver's trust in Level 1 and Level 2 automated vehicles [120]. Drivers' confidence in these vehicles is heavily influenced by their perception of the reliability and transparency of the systems, as well as their understanding of the capabilities and limitations of the automation [129]. Manufacturers play a key role in building trust by ensuring the reliability and performance of the automated systems [121]. Regulatory bodies, on the other hand, establish industry-wide safety standards and regulations that can enhance trust by providing a sense of oversight and accountability [88]. Effective communication and education about the technology are also essential in addressing concerns and overcoming skepticism. Ultimately, the trust built over time through positive experiences and the implementation of comprehensive training and education programs can further enhance trust in these vehicles.

3.4.2 CHALLENGES IN BUILDING DRIVER'S TRUST

Challenges in building driver's trust in Level 1 and Level 2 automated vehicles have multifaceted origins [120]. First, the lack of standardization in automated systems creates uncertainty and inconsistency in driver expectations. Second, effective communication and education about automation are crucial in addressing driver concerns and dispelling misconceptions. Third, overcoming skepticism and fear of technology requires a concerted effort to showcase the safety and reliability of these automated systems [118]. Fourth, building trust over time is essential through positive experiences, where drivers feel confident and comfortable relinquishing control to automation. Lastly, addressing concerns about system failures and malfunctions is paramount to fostering trust. By addressing these challenges, we can work towards enhancing driver's trust in Level 1 and Level 2 automated vehicles.

3.4.3 STRATAGIES TO ENHANCE DRIVER'S TRUST

3.4.3.1 IMPROVING SYSTEM RELIABILITY AND PERFORMANCE

Improving system reliability and performance is a critical factor in enhancing driver's trust in Level 1 and Level 2 automated vehicles [120]. Reliability ensures that the automated systems consistently function as intended, without unexpected failures or malfunction [130]. By minimizing system errors and glitches, manufacturers can instill a sense of confidence in drivers [109]. Additionally, enhancing performance involves optimizing system response time, accuracy in decision-making, and adaptability to various driving conditions [124]. A reliable and performant automated system not only reduces the likelihood of accidents caused by automation but also reinforces the driver's trust in the technology.

3.4.3.2 ENHANCING TRANSPARENCY IN SYSTEM DECISION-MAKING

Enhancing transparency in system decision-making is crucial for building and maintaining driver's trust in Level 1 and Level 2 automated vehicles [109]. By providing clear and accurate information about the system's operation and decision-making processes, manufacturers can help drivers develop a better understanding of automation capabilities and system limitations [125]. Transparency also involves addressing concerns about system failures and malfunctions, as well as overcoming skepticism and fear of technology [131]. Building trust over time through positive experiences is another effective strategy [120]. By implementing these measures, manufacturers can enhance transparency and foster trust, thereby increasing compliance with automated systems, promoting driver engagement and vigilance, encouraging acceptance of system recommendations, and improving willingness to relinquish control to automation. Ultimately, enhancing transparency in system decision-making is essential for ensuring the successful adoption and acceptance of Level 1 and Level 2 automated vehicles.

3.4.3.3 PROVIDING CLEAR AND ACCURATE INFORMATION TO DRIVERS

Providing clear and accurate information to drivers is crucial in building their trust in Level 1 and Level 2 automated vehicles [88]. Drivers need to have a complete understanding of how these systems operate and what their capabilities and limitations are [132]. Transparent communication about system reliability and performance is essential to ensure drivers feel confident in relying on the automation [122]. Furthermore, manufacturers and regulatory bodies play a significant role in establishing trust by providing accurate information and addressing concerns about system failures and malfunctions [133]. Effective communication and education programs can help alleviate skepticism and fear of technology, allowing drivers to have more positive experiences and build trust over time [134]. By focusing on clear and accurate information, the industry can enhance drivers' trust in Level 1 and Level 2 automated vehicles.

3.4.3.4 OFFERING COMPREHENSIVE TRAINING AND EDUCATION PROGRAMS

Offering comprehensive training and education programs is crucial in building and enhancing driver's trust in Level 1 and Level 2 automated vehicles [19]. By providing drivers with thorough training and education, they can develop a deeper understanding of the capabilities and limitations of automated systems [135]. This knowledge improves their perception of the technology and increases their confidence in relying on automation [11]. Additionally, comprehensive training programs can address any concerns or skepticism drivers may have, ensuring they feel adequately prepared to engage with and relinquish control to automated systems [104]. Moreover, education programs can help drivers navigate system failures or malfunctions, minimizing anxiety and promoting a sense of trust in the technology. Ultimately, offering comprehensive training and education programs is an effective strategy to build and maintain driver's trust in Level 1 and Level 2 automated vehicles.

3.4.3.5 ESTABLISHING INDUSTRY-WIDE SAFETY STANDARDS AND REGULATIONS

Establishing industry-wide safety standards and regulations is crucial for building and maintaining driver's trust in Level 1 and Level 2 automated vehicles [120]. Standardization plays a key role in ensuring that automated systems meet consistent safety requirements, reducing the likelihood of system failures and malfunctions [135]. With clear safety standards in place, manufacturers can instill confidence in drivers regarding the reliability and performance of automated systems [8]. In addition to safety standards, effective regulations are needed to oversee the development and deployment of automated vehicles. These regulations can address concerns such as liability, cybersecurity, and data privacy, further enhancing trust in the technology. By establishing industry-wide safety standards and regulations, stakeholders can work towards creating a trustworthy and sustainable ecosystem for Level 1 and Level 2 automated vehicles.

3.4.4 MEASURING TRUST

The dynamics of trust between drivers and automated driving systems are pivotal in shaping the acceptance, adoption, and safe deployment of these systems on roads. The references provided offer diverse perspectives and methodologies aimed at understanding, assessing, and quantifying the intricate construct of trust in automated systems from the driver's standpoint.

Nordhoff et al. (PLOS ONE, 2023) [136] delve into the assessment of driver trust in automated systems through the lens of psychometric scales and questionnaires. These instruments aim to quantitatively measure subjective perceptions and attitudes regarding automated driving systems. By potentially utilizing established frameworks like the Technology Acceptance Model (TAM) or Trust in Automation Scale (TAS), researchers can assess drivers' perceived reliability, effectiveness, ease of use, and overall trust in automated systems.

Similarly, the AAA Foundation for Traffic Safety (2021) [137] embarks on a comprehensive investigation into users' trust in automated driving systems. Employing rigorous survey methodologies, structured questionnaires, and possibly interviews, this study seeks to elucidate drivers' confidence, concerns, and underlying factors shaping their trust in automated systems. This qualitative approach aims to capture nuanced perspectives, psychological factors, and situational contexts influencing trust in automation.

Zaidi et al. (Springer, 2020) [138] contribute insights into the domain of trust in human-robot interaction, offering implications for driver-automation interactions. Their study explores the multifaceted nature of trust, encompassing factors such as system performance, reliability, transparency, and user interface design. While not explicitly presenting formulas, their analysis likely involves statistical methods to establish correlations between system performance metrics and perceived trust levels.

In an intriguing exploration of trust dynamics in human-automated vehicle interactions, Son et al. (arXiv, 2019) [139] introduced a mathematical model grounded in game theory. This model represents the intricate interactions between drivers and automated systems, potentially incorporating variables that represent perceived risk, system reliability, human decision-making parameters, and environmental contexts. The model's mathematical framework might simulate trust evolution in human-automated vehicle interactions, offering insights into the dynamics of trust over time and in varying scenarios.

While explicit formulas or mathematical expressions may not be presented in these papers, the methodologies to measure trust often encompass a combination of quantitative and qualitative approaches. Quantitative methods involve the use of psychometric scales, Likert-scale-based questionnaires, and statistical analyses to quantitatively measure drivers' perceptions and attitudes toward automated systems. Qualitative methods rely on interviews, surveys, and qualitative data analysis to capture the nuanced dimensions of trust and the underlying factors influencing it.

The multidimensional nature of trust measurement involves considering various factors, such as perceived system reliability, effectiveness, ease of use, transparency, and the contextual environment. These factors are often quantified through weighted scoring, regression models, or composite indices, integrating multiple aspects of driver perceptions toward automated systems.

In synthesis, the amalgamation of these diverse methodologies underscores the complexity and importance of measuring driver trust in automated systems. Integrating psychometric scales, qualitative insights, statistical analyses, and mathematical modeling, these studies contribute to understanding the multifaceted interplay between human perceptions and the adoption of automated systems in the realm of transportation.

3.5 DRIVER'S ATTENTION

With increasing automation, it becomes even more important for the driver to remain engaged and attentive [140]. Distractions inside the vehicle, such as smartphones, can divert the driver's attention from the road [141]. Moreover, external distractions, like billboards or other vehicles, can also affect their focus [142]. Fatigue and drowsiness are additional factors that can hinder the driver's attention [123].

To address these issues, driver monitoring systems play a vital role [142]. These systems serve the purpose of continuously monitoring the driver's behavior and alertness level [143]. Different types of driver-monitoring systems exist, each with its own set of functionalities [140]. However, challenges and limitations, such as false alarms or the inability to detect certain behaviors, also need to be considered [123].

The interaction between the driver and the vehicle is another significant aspect [141]. Effective communication design and human-machine interaction can impact the driver's attention positively [142]. Legal and ethical considerations are also crucial, as they determine liability and responsibility related to driver's attention requirements [143].

Moreover, training and education for drivers of automated vehicles are essential for understanding the specific skills and knowledge needed in different automation levels [141]. Safety implications are a major concern, and potential risks and hazards associated with driver distraction must be addressed with appropriate mitigation strategies to maintain driver's attention and overall vehicle safety [140].

Future developments and challenges include advancements in automation technology and the integration of artificial intelligence in driver monitoring [142]. Addressing user acceptance and trust issues is also paramount [123]. In conclusion, driver's attention in automated vehicles is critical for safe and effective operation, and it requires ongoing research and development to ensure its optimization [142].

3.5.1 FACTORS AFFECTING DRIVER'S ATTENTION

Factors affecting driver's attention in level 1 and level 2 automated vehicles include distractions inside the vehicle, external distractions, and fatigue and drowsiness. Distractions inside the vehicle can be caused by various factors such as mobile devices, infotainment systems, or passengers [144]. External distractions, on the other hand, can come from the surrounding environment, such as billboard advertisements or other vehicles [145]. Fatigue and drowsiness are also significant factors that can impair the driver's attention and response time [146]. These factors need to be carefully considered and addressed to ensure the safe operation of automated vehicles. Effective driver monitoring systems can play a crucial role in detecting and mitigating the impact of these factors on the driver's attention [142].

3.5.1.1 DISTRACTION INSIDE THE VEHICLE

Distractions inside the vehicle play a significant role in determining the driver's attention in Level 1 and Level 2 automated vehicles [147]. These distractions can divert the driver's focus from the road, leading to potential safety risks. Factors such as mobile phones, infotainment systems, and passengers can contribute to these distractions [148]. Understanding and identifying these distractions is crucial for designing effective driver monitoring systems [142]. By recognizing the specific distractions inside the vehicle, manufacturers can develop strategies to mitigate them and improve the overall safety of automated vehicles [149].

3.5.1.2 EXTERNAL DISTRACTIONS

External distractions play a significant role in the driver's attention in both Level 1 and Level 2 automated vehicles (Singh & Kathuria, 2021). These distractions, originating outside the vehicle, divert the driver's focus from the road and can decrease their ability to respond to potential hazards. Examples of external distractions encompass other vehicles, pedestrians, advertising billboards, and environmental factors such as weather conditions [144]. These distractions, whether visually or auditorily stimulating, cause drivers to shift their attention away from the task of driving. As the level of automation increases, it becomes even more important to address and minimize these external distractions to ensure the continued safety and effectiveness of automated driving systems [149].

3.5.1.3 FATIGUE AND DROWSINESS

Fatigue and drowsiness are significant factors that can affect driver's attention in Level 1 and Level 2 automated vehicles [150]. When drivers are fatigued or drowsy, their ability to stay alert and respond to potential hazards is compromised [140]. This can lead to delayed reaction times and an increased risk of accidents. It is crucial to address these issues to ensure the safety and effectiveness of automated vehicles. Driver monitoring systems play a vital role in identifying and mitigating fatigue and drowsiness [152]. These systems monitor various indicators such as eye movements, head position, and facial expressions to determine the driver's level of attentiveness [151]. By detecting signs of fatigue or drowsiness, the system can alert the driver and even intervene to prevent accidents. However, there are challenges and limitations associated with driver monitoring systems, such as false alarms and the need for continuous calibration [150]. Overcoming these challenges and improving the accuracy and reliability of driver monitoring systems is essential for the successful implementation of Level 1 and Level 2 automation.

3.5.2 DRIVER MONITORING SYSTEMS

Driver monitoring systems play a vital role in ensuring the safe operation of Level 1 and Level 2 automated vehicles [140]. These systems are designed to continuously monitor the driver's attention and engagement with the driving task [153]. The purpose of driver monitoring systems is to detect and alert any signs of driver drowsiness, distraction, or disengagement, allowing for timely intervention if necessary [154]. There are various types of driver-monitoring systems available, ranging from camera-based systems that track the driver's head and eye movements, to sensor-based systems that detect physiological indicators of attention [155]. However, there are also challenges and limitations associated with these systems, including issues with accuracy, false alarms, and the potential for driver misuse or circumvention [140].

Future developments in automation technology, such as the integration of artificial intelligence in driver monitoring, hold promise for enhancing the effectiveness and reliability of these systems [153]. To improve driver attention in automated vehicles, it is crucial to address these challenges and limitations while considering legal and ethical considerations, providing comprehensive driver training, and implementing mitigation strategies for maintaining driver attention [155].

3.5.2.1 PURPOSE AND FUNCTIONALITY OF DRIVER MONITORING SYSTEM

Driver monitoring systems are designed to monitor the driver's attention and alertness while driving [143]. The purpose of these systems is to ensure that the driver remains engaged and ready to take control of the vehicle when necessary [156]. They utilize various sensors and cameras to track the driver's eye movements, head position, and other physiological indicators of attention [157]. Additionally, driver monitoring systems can detect distractions inside and outside the vehicle, as well as signs of fatigue and drowsiness [140].

Despite their functionality, these systems also have challenges and limitations that need to be addressed for more effective implementation [156]. Understanding the purpose and functionality of driver monitoring systems is essential for improving driver's attention in automated vehicles [143].

3.5.2.2 TYPES OF DRIVER MONITORING SYSTEMS

Driver monitoring systems play a crucial role in ensuring the safe operation of Level 1 and Level 2 automated vehicles [140]. These systems are designed to continuously monitor the driver's attention and detect any signs of distraction, fatigue, or drowsiness [158]. There are several types of driver-monitoring systems available, each with its own set of features and capabilities [159]. One common type is the gaze tracking system, which uses cameras to track the driver's eye movements and determine their level of engagement with the driving task [160]. Another type is the facial recognition system, which analyzes the driver's facial expressions to identify signs of distraction or drowsiness [140]. Additionally, some driver monitoring systems can also monitor other physiological parameters such as heart rate and brain activity [158].

Despite their potential benefits, driver monitoring systems face challenges and limitations, such as the difficulty in accurately detecting driver distraction or drowsiness and the potential invasion of privacy [159]. As automated vehicles continue to evolve, it is important to address these challenges and develop more advanced and reliable driver monitoring systems to ensure the safe operation of these vehicles [160].

3.5.2.3 CHALLENGES AND LIMITATIONS OF DRIVER MONITORING SYSTEMS

Driver monitoring systems play a crucial role in Level 1 and Level 2 automated vehicles but come with certain challenges and limitations. One major challenge is the need for accurate and reliable detection of driver attention. While existing systems can monitor the driver's gaze, head position, and eye movements, they may not be able to accurately assess the driver's cognitive workload or level of attention, which can impact the effectiveness of the automation. Another limitation is the potential for false positives or false negatives, where the system may incorrectly detect inattentiveness or fail to identify instances when the driver is not paying attention. This can lead to unnecessary interventions or missed opportunities for the system to intervene and prevent accidents.

Additionally, the design and implementation of driver monitoring systems need to consider factors such as driver privacy, driver acceptance, and user interface design to ensure that they are effective and accepted by users. Overcoming these challenges and limitations will be crucial in improving the overall safety and performance of automated vehicles.

3.5.3 MEASURING DRIVER'S ATTENTION AND DISTRACTION

Understanding and measuring driver attention is critical in ensuring road safety and enhancing the efficiency of transportation systems. With the increasing integration of technology into vehicles and the growing concerns regarding distracted driving, research efforts have been directed towards assessing and understanding drivers' attention levels. This essay delves into the methodologies and approaches used for measuring driver attention, drawing insights from various scholarly articles and research papers.

Eye-tracking technology has emerged as a pivotal tool in studying driver attention. Véras et al. (2022) [161] highlighted the significance of eye-tracking systems in detecting drivers' attention levels. By monitoring gaze patterns and fixation durations, researchers can gain insights into where drivers focus their attention within the vehicle environment. This technology provides valuable data on visual attention, allowing researchers to analyze drivers' eye movements and understand the allocation of visual resources during driving tasks.

Furthermore, Ojsteršek and Topolšek (2019) [162] emphasized the influence of both visual and cognitive attention on drivers' perception of changes in the traffic environment. Cognitive attention, encompassing mental workload and cognitive processing, complements visual attention in shaping drivers' awareness of their surroundings. Understanding the interplay between these attentional aspects is crucial for devising interventions to mitigate distraction and improve drivers' situational awareness.

The integration of advanced computational methods has also significantly contributed to measuring driver attention. Gou, Zhou, and Li (2022) [164] proposed a driver attention prediction model based on convolutional and transformer architectures. This approach utilizes machine learning techniques to analyze various data inputs, such as visual cues and behavioral patterns, to predict drivers' attention levels. By leveraging computational models, researchers can explore complex data sets and derive predictive insights, aiding in the development of proactive attention monitoring systems.

Moreover, Kircher and Ahlstrom (2018) [165] evaluated different methods for assessing attention during driving tasks. Their study underscored the significance of diverse assessment techniques, including physiological measurements, behavioral observations, and subjective self-reports. Integrating multiple assessment methods allows for a comprehensive understanding of drivers' attentional states, enhancing the accuracy and reliability of the measurements obtained.

In conclusion, measuring driver attention encompasses a multidimensional approach involving the integration of eye-tracking technology, cognitive assessments, computational models, and diverse measurement methodologies. By leveraging these tools and methodologies, researchers can gain a holistic understanding of drivers' attentional states, thereby paving the way for the development of effective interventions and technologies aimed at enhancing road safety and optimizing driving experiences.

4 DISCUSSION AND SCOPE FOR FUTURE WORK

The advent of Level 1 and Level 2 automated vehicles mark a paradigm shift in transportation, promising increased safety and efficiency. Central to the success of these advancements is the intricate interplay between driving assessment and human-machine interaction metrics. Understanding the pivotal role of the human factor in these automated systems, a fusion of metrics encompassing both driving assessment and human-machine interaction emerges as an imperative approach.

Driving assessment metrics in the context of automated vehicles extend beyond traditional performance evaluation. They now intertwine with human-machine interaction metrics, recognizing the indispensable influence of human behavior and decision-making in the operation of these semi-automated systems. Crucially, these metrics converge in shaping the safety landscape of Level 1 and Level 2 automated vehicles.

At the forefront of this integration lies the evaluation of user engagement. Metrics designed to discern the degree of driver involvement during automated driving phases fuse driving assessment elements like attention allocation with human-machine interaction cues, such as responsiveness to in-vehicle prompts. Real-time monitoring, combining physiological sensors and interface interaction data, becomes paramount in gauging and ensuring driver engagement levels conducive to safe operation.

Adaptability and trust metrics form another crucial facet. The seamless transition between automated and manual driving modes necessitates metrics assessing the driver's adaptability and trust in the system. Understanding how quickly and effectively users assume control when required, coupled with analyzing instances of driver-initiated system overrides, provides insights into the evolving trust dynamics and adaptability of users within these semi-automated environments.

Furthermore, cognitive workload assessment metrics intertwine driving assessment factors like task complexity with human-machine interaction data to measure the cognitive load imposed on drivers. This assessment is critical in delineating situations where automation handover or takeover may lead to heightened cognitive workload, thereby informing system design enhancements for optimal user experience and safety.

Communication effectiveness metrics become instrumental in evaluating the clarity and comprehension of information exchanged between the automated system and the driver. The speed and accuracy with which users interpret system messages, alongside their response efficacy, dictate the effectiveness of human-machine communication, fostering a safer operational environment.
Training and familiarity metrics complement this fusion by evaluating the impact of training programs on driver understanding and utilization of automated features. Assessing user familiarity with automation capabilities aids in understanding how drivers engage with and monitor automated systems over time, contributing to improved system usability and safety.

An intrinsic component of this integration involves analyzing human-centric errors within automated driving contexts. Metrics identifying and analyzing human errors, including misinterpretations or delayed responses, serve as a blueprint for refining human-machine interfaces. This data informs interface designs that mitigate potential errors and foster safer interactions between users and automated systems.

In conclusion, the combination of driving assessment and human-machine interaction metrics serves as the cornerstone in establishing a comprehensive safety framework for Level 1 and Level 2 automated vehicles. This holistic approach, accounting for the dynamic interplay between human drivers and evolving automation, not only fosters safer operational environments but also propels advancements in user-centric design, ensuring the realization of the transformative potential of automated transportation.

5 CONCLUSION

This comprehensive review serves as a critical exploration into the realm of safety metrics concerning Level 1 and Level 2 automated vehicles, consolidating recent literature to highlight pivotal aspects of driving assessment and human-machine interaction. The meticulous examination of these factors underscores their paramount importance in establishing robust metrics and regulatory frameworks necessary for the safe operation of these vehicles in modern transportation systems.

Throughout the review, an intricate analysis of driving assessment and human-machine interaction revealed their multifaceted nature, shedding light on their significance, existing challenges, and the methodologies proposed by various studies. The emphasis on understanding these nuanced dimensions aims to guide informed decision-making, crucial in shaping regulations and safety protocols for automated vehicles.

Furthermore, the identification of research gaps within the collated literature underscores the need for continued exploration in specific areas. This examination not only consolidates existing knowledge but also emphasizes the necessity for holistic safety metrics that encompass the diverse facets of automated vehicle operations. By addressing these critical gaps, the aim is to contribute to the development of safer and more efficient transportation systems.

Ultimately, this comprehensive review serves not only to consolidate current understandings but also to direct attention towards essential areas requiring further investigation. It provides a roadmap for advancing safety metrics and regulations tailored specifically for Level 1 and Level 2 automated vehicles, aiming to enhance their safe integration and operation within contemporary transportation landscapes.

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