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AI-Driven Systems for Improving Autonomous Vehicle Adaptability

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1. Introduction

Current interest in and research attention to artificial intelligence (AI)-driven systems has been increasing, especially as applied to autonomous vehicles. The demand for vehicles built based on AI technology has also been growing. The adaptability of autonomous vehicles is indispensable for improving vehicle performance and safety. To meet the requirements for intelligent adaptability, an accurate understanding of autonomous vehicles, with the help of intelligent systems, should be incorporated. This will also increase public confidence in autonomous vehicles. Semi-autonomous and autonomous vehicles are being developed and will be in commercial operation soon. This development is not possible without the use of AI to enhance their technical capabilities.

In response to this, traditional architectures and systems are being revamped to cater to the required capabilities. To build intelligent autonomous vehicles, it is crucial to integrate an AI system because the AI-connected car system will change traditional vehicles into intelligent automated driving models. However, AI-driven systems may face challenges in functioning better and providing personalized features to their users. It is necessary to utilize advanced technologies to encounter these challenges and gain extreme performance. Vehicles need adaptive intelligence to ensure the comfort and safety of their passengers and also to enhance highway safety. To adapt the vehicles based on the surrounding environment and passengers' biometrics, an AI-driven learning system is attributed and integrated into various intelligent expertise. The real-time learning functionality of AI autonomous vehicles generates dynamically changing intelligence. The background is analyzed, which introduces a historical overview of automated vehicles and adaptive modeling. The main research contributions and findings are presented. The subsequent structure is also presented that includes four main points. Finally, the main research components are concluded.

1.1. Background and Significance

Over the last few decades, there has been substantial progress in the development of autonomous vehicles as elements of intelligent systems such as robots and cyber-physical systems. Technological advancements, particularly in the fields of data processing and machine learning, have made it possible to develop AI-driven systems that significantly enhance their adaptability in real-world settings. As such, there is a need to explore the deployment of such technologies in new applications such as transportation, industry, and defense. Autonomy in transportation enhances the ability of vehicles to make driving decisions based either on information obtained from their environment and design objectives or from machine learning with respect to their sensors and environment. This information makes it possible to maximize the continuous, safe, and efficient flow of traffic at any given time. It provides the capacity to hit the narrow window of optimal system throughput when the maximum system potential changes as a result of a decrease in time headway or local speed limit.

Moreover, vehicle automation significantly enhances safety by reducing the number of crashes, injuries, and fatalities in transportation. Autonomous vehicles will provide mobility to so-called "transportation-disadvantaged" or "non-drivers," including the visually and physically impaired as well as the elderly, but a significant proportion of them will use fully autonomous services. Autonomous vehicles offer a spectrum of freedom to passengers who could drive or could be driven. AI systems have been argued as the missing piece that will allow such indoors-only autonomous systems to have very low latency when modifying trajectories or selecting alternate routes in a dynamic environment. Furthermore, at the international level, there is significant interest in the regulation of autonomous system deployments, particularly in the field of transportation. Countries have, or soon plan to have, regulatory frameworks on engineering and designing connected and autonomous vehicles on their roads. As such, the public perception of stringent safety standards must be recognized when discussing the social acceptability aspect of the technology. Public acceptability, and subsequently trust, is seen as essential for the successful deployment of automated vehicles. Our interconnected system model integrates human trust acceptance and behavior into the system model, and an improvement in the level of human trust within the overall system will also ultimately lead to an increase in the demand for such a system.

1.2. Research Aim and Objectives

Following from the description provided in Section 1.1, the overall aim of this research is to explore the development of AI-driven systems to enhance the adaptability of an autonomous vehicle system. To guide this research, the following objectives are proposed: Identify the parameters of the dynamic environment that have the most impact on vehicle system performance. Once identified, design appropriate learning algorithms to detect, interpret, and learn the inherent temporal patterns in the identified dynamic parameters and their operational impacts. This will allow the system to prioritize the state changes and act to ensure safe operation. Develop methods and control strategies that leverage the prioritization and rate of change techniques used by the adaptive layer. Evaluate the proposed system to determine the trade-off between adaptability and operational efficiency, particularly with respect to the thresholds for actuation designed to minimize potential performance compromises. The primary aim of this proposed research is to critically assess current state-of-the-art techniques and research limitations to identify the need for and possible approaches to developing novel AI-driven systems to enhance autonomous vehicle adaptability. The fundamental objectives of this research are to establish appropriate methodological approaches to the operationalization of the artificial intelligence technologies available to enhance the adaptability of autonomous systems by improving their capacity to detect and act upon unexpected environmental changes, and to actively contribute novel datasets and insights to the academic literature on autonomous systems adaptability as they grow to scale. Should a successful outcome occur, the research is likely to contribute significantly to the potential practicality of autonomous vehicle operation. It could address controversial concerns regarding road safety and survivability in unpredictable conditions and could impact regulatory innovation on connected and autonomous vehicle systems. This work aligns with the national project and recent innovation in autonomous shuttle bus road testing. The safety of these new technologies, even in low-speed confined environments, is a topic of ongoing public concern, and the proposed research will contribute strongly to this national effort, since it addresses autonomous vehicle safety issues in a road system not separated from pedestrians and cyclists.

2. Fundamentals of Autonomous Vehicles

Autonomous vehicles refer to intelligent machines with the ability to perform essential functions such as braking, acceleration, and steering, while simultaneously making decisions and handling uncertain environments and road conditions through a range of active sensors and algorithms. The automated vehicle system can be designed using diverse algorithms and techniques, and it deals with many instruments like sensors, actuators, and adaptive control algorithms suitable for managing control systems that transform the position goals or points of interest from the sensors into steering commands after performing sensing and interpreting its real environment and control input requirements. The concept of autonomous vehicles is defined as a vehicle that can perform the dynamic driving tasks of a human driver in the most challenging driving domain and is capable of responding to any unsafe situation to automate interoperability. The concept involves gathering information from the environment through sensors and processing this information at a central point, followed by applying suitable algorithms to ensure the desirability of the output, referred to as "Data Input - Information Processing - Decision Output - Action." The safety analysis of AVs often requires modeling, design, and validation of different functions and dynamic behaviors of the artificial system. In this context, various regulatory agencies have focused on different areas concerning autonomous or intelligent vehicles.

2.1. Definition and Components

An autonomous vehicle (AV) can be defined as a vehicle that is capable of functioning without human intervention. The capability is achieved via the integration of several hardware and software components, namely sensors, computing technologies, actuating systems, and software algorithms. Sensors are utilized to perceive the surrounding environment of the vehicle, while the computing technologies process the sensor data and generate decisions in terms of vehicle navigation. The processed information from sensors is utilized to define obstacles and free spaces around the vehicle, which eventually guides its movements and decision-making processes.

One of the key elements in an autonomous vehicle system is simultaneous localization and mapping (SLAM). It is a method and software algorithm used to construct a map by utilizing a single robot or a vehicle that navigates in an unknown environment and at the same time tracks its position. The algorithms that are used in SLAM are complex and have a higher rate of computational intensity. The processing of all these algorithms and obstacles is achieved by using computing technologies, such as central processing unit or graphical processing unit with programming languages. Various sensors such as cameras, Lidar, and radar are used to capture the surrounding environment. These sensors are essential for the sensing and perception of the AVs. Cameras have a wide viewing angle and a higher resolution compared to Lidar systems, while Lidar sensors provide depth information in the form of point clouds that can be used for planning purposes.

The development of software and incorporation of these hardware systems in a manner that allows them to function harmoniously is a complex process. Hence, the development of an AV is a difficult and laborious task. Autonomous vehicles can be broadly classified into two categories, namely public transport autonomous vehicles, usually called autonomous buses or driverless taxis, and private-customized autonomous vehicles. Moreover, the functionality of autonomous vehicles can be categorized depending on the level of automation, such as parking, highway, and full automation. The transition to fully autonomous technology from manual requires artificial intelligence, connected devices, and software that provide high levels of human intuition and emotions. A well-balanced AV will result in a disruption of the automobile market, allowing for greater comfort, improved overall user experience, and a reduction of accidents. The vehicle market is moving towards a bidirectional flow of assets and services among users and stakeholders.

3. AI-Driven Systems in Autonomous Vehicles

This report tries to provide an overview of AI or machine learning-based approaches that are used in autonomous vehicles. Therefore, in this section, we discuss how artificial intelligence is integrated into autonomous robotics. The intersection of AI with robotics has significantly improved the performance of robotic systems with its ability to enable real-time processing decisions. Autonomous or AI-driven systems usually use some techniques from AI, such as machine learning and deep learning, to make sophisticated and real-time decisions for the environment where they are working. In the domain of autonomous vehicles, different AI techniques such as perception, planning, and control are used for realistic applications, as they help in learning and understanding the interaction of different components across various environmental setups. AI techniques integrated into perception aim at improved detection and classification of objects, trajectory prediction, feedback loops, and complex interpretability. Advanced AI algorithms integrated with the components of planning and control allow autonomous vehicles to drive through complex navigation, traffic jams, density, and dynamic behaviors of different elements in the environment. Different from algorithms mentioned earlier, AI-driven systems provide continuous learning by using data points from the feedback loop that improve model performance. For an autonomous vehicle that drives into the real-world environment, data-driven approaches make it more adaptable to environmental interactions and factors, improving the accuracy and reliability of the vehicle. Arguably, these characteristics also make things better for using machine learning-driven systems in autonomous cars. Unfortunately, there are a few concerns with the use of machine learning-driven systems in autonomous vehicles. Besides the ethical concerns associated with any machine learning-driven algorithm, it is really hard to develop a robust machine learning-driven system that generalizes well in an application as complex as an autonomous vehicle. In short, there is a debate on the actual benefits as opposed to the challenges of the AI-driven technique in autonomous vehicles. However, for a direction selection, we'll proceed believing that AI can be used to enhance the accuracy of different modules in autonomous vehicles.

3.1. Overview of AI Technologies

AI models are a popular and equally essential tool for autonomous vehicles. Machine learning, a branch of AI, consists of various statistical methodologies for the development of artificial neural networks which resemble human brain networks. Deep learning is a subset of machine learning that uses unsupervised learning of features and classifiers. Neural networks, and especially deep learning, have gained popularity due to their capabilities to process and apply the results of processing automatically after being fed with vast datasets. Moreover, computer vision tools interpret visual data and process it into information that can be used to interpret and understand the surrounding environment.

The resulting data and information from these technologies contribute to the adaptive behavior of autonomous vehicles. Sensor fusion or multi-sensor data fusion is another technology that relies on AI. Data from multiple sensors, including LiDAR, cameras, and radar sensors, are combined and processed to result in new and improved data values, and ultimately, they provide a complete overview of the vehicle's environment. The ability to adjust to the surroundings in anticipation of change and inconsistencies constitutes adaptability. In autonomous vehicles, these technologies give rise to predictive analytics that help predict the actions of other road users. Every autonomous vehicle means a reduction in the possibilities of human-related errors in traffic and in the saving of operating costs that are spent due to vehicle downtime, traffic congestion, and so on. Additionally, the application of AI in the automated driving of vehicles connects to the advancement of information and communication systems. In conclusion, all of these newly introduced AI technologies are expected to accelerate the implementation of autonomous vehicles on public roads.

However, the real-time implementation of these AI technologies is still a challenge for edge computing-related tasks. The main challenge attached to real-time analysis is the computational time. The computational time becomes significant when run through the edge computers. Moreover, the large databases required for the training of artificial neural networks are another hindrance. Such databases are collected due to the real-life operations of autonomous vehicles. Nonetheless, new advances and trends towards the exploration of technology should be realized. New models of the AI-driven perception, prediction, and planning system improve both the vehicle's safety and efficiency and greatly improve autonomous vehicle operations.

4. Machine Learning Techniques for Improving Adaptability

Machine learning and, in general, artificial intelligence (ML/AI) methods have enabled many autonomous driving systems to adapt their behavior to better cope with the fluidity of real-world driving environments. The learning of these systems can be thought of as their ability to improve decision-making based on their exposure to the environment, data, and experiences. In this way, the learning of AI/ML algorithms provides a direct route to making autonomous vehicles more adaptable. There exist many ways to categorize different approaches within the broad area of ML. From an automotive perspective, we can posit that there is one key differentiator between all ML approaches with respect to their relevance to the adaptability of autonomous systems: their ability to process the feedback loop and improve with experience.

Progressive abilities to learn can take on the intensity of face value, from the most direct supervision of behavior to the most indirect and philosophically motivated ideals. Thus, these can be categorized into (1) supervised, (2) unsupervised, and (3) reinforcement learning methods. Because there is confounding between approaches that learn from explicitly human-defined objectives and those that do not, we do not progress in intensity of learning with the above categorization, and assume the ultimate form of AI will be to learn from raw experience with absolute freedom from human guidance. Each method can have varying degrees of fidelity to real-world complexity. We thus learn the more in-depth principles and pitfalls of adaptive AI methods from the less-restrictive, more philosophically robust end back to the most immediate. Optimal adaptability may require systems that learn using continuous learning algorithms. In this brief, we approach each of the above kinds of learning in turn, detailing a few techniques that contribute to adaptability. These techniques include more abstract frameworks that underpin approaches rather than concrete algorithms, providing relevant insights that contribute to adaptability. We close out by describing direct insights and in-depth approaches.

4.1. Supervised Learning

Supervised learning is a machine learning technique that trains the autonomous vehicle on a labeled dataset to learn patterns and make predictions. The labeled dataset contains a series of variables or 'attributes' that are used to determine an outcome. These attributes are closely related to the features or states of autonomous vehicles, and the outcome is to determine how an autonomous vehicle should respond or adjust in a given scenario. A scenario may contain information about weather conditions, data on the type or behaviors of other road users, road and traffic conditions, or other such events and occurrences. Learning occurs when the autonomous vehicle uses these labeled attributes to learn relationships and effects to determine actions, such as steering angle, speed, or acceleration. Many algorithms help the autonomous vehicle learn from being given a set of labeled historical data, whether it is about a navigation scenario, an intended lane change, or overtaking another road user. These algorithms fall under the two main classes of classification and regression tasks. While classification algorithms help in determining categorical responses for predefined training classes, regression algorithms determine a continuous-valued output to support vehicles in their decision-making. Using supervised techniques for vehicle adaptability makes the vehicle's decisions more sensitive to different situational and environmental factors, hence enhancing adaptability in the vehicle's response. This is experienced in the vehicle's effectiveness in decision-making and the robustness of driving policy. Compared to other learning techniques, under supervised learning, the autonomous vehicle will have a high-quality, highly accurate, reliable response both in normal and extreme driving conditions.

4.2. Unsupervised Learning

Unsupervised learning, in the absence of ground-truth data, represents an approach that is highly complementary to supervised learning. This form of AI models can gain insight into the data from which patterns are to be unveiled without the necessity of specifying explicit outcomes. Unsupervised techniques aimed at discovering hidden structures include clustering, providing a solution to categorization problems, and association algorithms focusing on finding associations, correlations, or coherent relationships among entities. The main benefit of using unsupervised algorithms lies in the ability of an intelligent system to be sensitive to unexpected changes without the need to be retrained. The method can also be viewed as an augmenting signal, allowing the system to build situational awareness. However, there exist practical limitations in the adoption of this approach. The principal issues arise in interpreting the mined outcomes or maintaining the stability of the adapted model.

Integrating the unsupervised models within the vehicle means extensive and elaborate studies to derive a mechanism that will allow an effective shift between the representation subspaces, i.e., establishing context-based mappings. However, in case no prior information about the outcomes, including the errors, is available, which will be difficult to access due to the lack of ground truth information about the range of states of being in another context, the results of clustering need to be carefully interpreted. Both form, distribution, and the number of clusters are the actual outputs, and the extension to more complex clustering schemes that outperform the traditional overfitting rule selection of potential outcomes should be treated cautiously. Those obstacles discussed above need to be tackled in order to fully embrace the full potential of unsupervised learning for AV systems. Overall, combining different learning paradigms has proved to provide an efficient solution for improving the adaptability of AVs.

4.3. Reinforcement Learning

Reinforcement Learning.

Reinforcement learning is one of the machine learning paradigms concerned with the development of decision-making systems. Rather than being programmed with explicit solutions, such systems are allowed to interact with their environment and learn the optimal action as a result of rewards and penalties. Despite the fact that the engagement paradigm may significantly differ in various applications, for autonomous vehicle systems, it is about learning how to drive by observing the environment and the quality of their actions. This is done by experimenting with a variety of actions and evaluating each one of them depending on their impacts on the surrounding environment. Several algorithms and frameworks have been introduced to enable intelligent decision-making based on reinforcement learning approaches. These algorithms provide the system with the ability to adapt its behavior in front of various driving and traffic scenarios, like making lane changes with respect to traffic jams or intersection lights and the driving of pedestrians.

Simulators can be a safe environment for testing reinforcement learning agents, particularly with respect to autonomous vehicle-related problems. They enable a learning agent to completely check out their implicit structures in decision-making actions and engage in "what-if" thinking in certain situations for which a sufficient amount of information is not easily accessible. In a nutshell, e-simulations of hypothetical future situations and their potential outcomes could be very useful in the process of learning and cognitive development and offer a mechanism for leveraging learning and real-time analysis. Simulation-enabled learning agents allow for the possibility of real, safe exploration of rich returns and interactive strategies. This means that the agent can learn from its actions and make continuous progress. More to the point, intelligent agents built with reinforcement learning have the capability of learning from experience acquired in environments of increasing complexity and the integration of new actions or adaptability in an entirely different environment. Nevertheless, the process of developing reinforcement learning mechanisms is faced with learning difficulty and stability problems. Furthermore, it requires several training episodes. In particular, the problem of efficiently balancing the exploration-exploitation mechanism, also known as having a strong series of encounters to determine which optimization works well and which does not, is a challenge for the development of a suitable training module. In the context of autonomous vehicle systems, reinforcement learning enhances adaptability in the developing system and maximizes vehicle engagement with the surrounding environments through personalized and optimized driving styles. In summary, reinforcement learning represents a true system for autonomous vehicle adaptability.

5. Case Studies and Applications

Several industry leaders are introducing new initiatives to leverage the increasing adaptability of AI-driven systems for their AVs. An evaluation of such a system in the SAE Level 4 Hyundai motor company AV, which relies on an accompanying safety plan, distinguishes between traditional engineering methods and AI methods that have the same goals, providing a comparison of these two methods. An adaptive AI decision-making system is proposed to improve the adaptability of AVs to different cities. The system recognizes the suitability of actions in different environments, handles unreliable information, and enables real-time autonomous decision-making. The proposed methods were evaluated in a real testbed across five US cities and a simulated testbed. The AI-driven AGV application aims to increase overall warehouse efficiency within a large logistics facility. The AGVs were trained for a specific set of tasks before being introduced into the facility. The AGVs improve adaptability to the new environment and handle the transition from usual operation to temporary, but recurring, disruptions.

From a research perspective, the consideration of driving priorities in the automated vehicle decision-making process can enable AVs to adjust to the user's driving style. An example of AV reconfigurability is provided by an experimental demonstration that significantly improved the performance of subjects carrying out a failing driver recovery task on a driving simulator. The desired effects were obtained robustly, and the amount of assistance implicitly scaled adaptively to a range of disturbances. In conclusion, despite the aspiration of putting AI in the driving seat of an AV, we appreciate that, actually, a number of AV operation-related tasks will continue to be defined from a top-down human perspective. These AV operation-related decisions may change in the future as more AV-driving field data is collected and the development in machine learning and AI continues. However, at this point in time, there are huge safety, efficiency, infrastructure, and liability challenges to changing the top-down design of the existing road traffic system.

5.1. Real-World Implementations

Examples of successful real-world implementations of AI-driven technology can be found. A system of AI driving, controlling, and planning functionalities was iteratively tested and improved at large scale, growing to manage fully driverless operations with a real rider service on operational public roads. Similarly, a truly end-to-end learning-based AI vision control system was designed and tested from the data center to a fleet of cars. These systems demonstrated better driving capabilities when compared to typical hand-designed architectures, accompanied by improvements in regard to low-level vehicle performance and simple on-road tests. Deep reinforcement learning methods were employed to handle the complete challenging task of deciding and acting in driving scenarios at various abstraction levels, from high-level route planning to low-level tactical choices for decision-making in vehicles without real drivers.

The deployment of such complex AI-driven systems at a worldwide scale also faced several hurdles, ranging from technological aspects to regulatory and safety concerns. A collaborative strategy was especially pursued with different stakeholders, including automotive industry experts, law enforcement, first responders, local passenger event review boards, and regulatory agencies, machine learning and systems safety experts from academia, and even industry consortiums working on safety and explicit decision and planning representation for autonomous vehicles. This early feedback helped to iteratively update the systems in order to adapt to a range of new modes of operation and improvement. It was revealed that these systems have driven into the millions of miles, equivalent to hundreds of years of human driving experience. Furthermore, a range of journalists were allowed to test the self-driving technology and document the experience. It was further claimed that the vehicles have the most human-like driving style.

5.2. Challenges and Solutions

AI-driven systems present significant challenges for implementation in the autonomous vehicle domain. For developers to deploy AI-driven systems in autonomous vehicles, significant development and validation work will be required to ensure their safe and effective integration. There are several high-level challenges that have been identified as those likely to have the largest impact on mission effectiveness, or the challenges gaining the attention of the public and regulators.

There is significant attention on the deployment of AI technologies in the autonomous vehicle space from the public and policymakers. Safety, public perception, and regulation are three challenges that are outside the technical realm, yet exert significant influence on the adoption of AI technologies into the autonomous vehicle domain. Integration of AI-driven systems into an autonomous vehicle's decision-making chain is scientifically and technically complex, and many sub-challenges must be addressed before these AI systems can achieve a low risk of high-severity failures. Data integration and quality, system robustness, trust ambiguity, safety model validation and verification, and combining AI systems with other technologies are technical challenges that have been identified as unique or given greater significance when applying AI in the autonomous vehicle domain. Several stakeholders have looked at the question of integrating AI-driven systems into autonomous vehicles in the context of the operational design domain and more broadly in the domain of transport systems. Best practices and key questions to be addressed when integrating AI have been identified.

A number of specialists in the autonomous vehicle sector have proposed activities and best practices to address some of the questions in the field of ethics and AI intervention technologies in the transport domain. These activities aim to foster collaboration between governments, the private sector, research institutions, and civil society to inform future policy decisions. AI ethics principles have also been proposed by some countries and organizations, where research in AI is actively promoting a focus on ethical AI. While leading testing and demonstration activities in autonomous systems have tackled different technical issues and acknowledged ethical and social concerns, the level of detail and advice offered varies. Any AI technology, including those for autonomous systems, must be cost-effective and provide long-term value to the user and system developer. A systems approach, engaging key stakeholders alongside operators and maintainers of autonomous vehicle systems, is therefore needed. When considering AI-driven systems, focusing on autonomous vehicle technology is likely to overemphasize potential solutions to the detriment of safety improvements in the system. Data sharing, especially in the context of the interaction between multiple autonomous systems, presents ethical and privacy concerns, particularly when the data of vulnerable road users is involved and consent cannot be obtained. Continuing research should investigate the expected increase in user trust and the willingness of road users to share information based on AI deployment and use, and how systems can continuously learn from these challenges to improve system reliability and user trust.

6. Future Direction

Through the section: We can say that machine learning and artificial intelligence are evolving areas in terms of providing detailed reasoning for generated functionality. Also, some of the latest papers show notable interest in the ethical aspects of autonomous cars and the requirement for related investigation in relation to architectural and sensor-driven solutions. In this way, these issues can be considered in the next step of the proposed research. Regulatory changes could be considered to adapt to the need for more precise strategies in a scenario where brands can impose solutions based on public technology. The current mission-oriented funding is a sign of the increasing influence of the private sector in pushing technologies into the market. Applications that simplify transport can reduce traffic, keep systems manageable, and contribute to safety. The involvement of companies moving in the field of data and advertisement with their private and public centers in locations where regulations allow access to such information will most likely allow up-to-the-minute mapping. As we move towards a more optimal market situation, cheaper innovation will also help in overcoming various logistic and social impacts of the fast advancements involving most manufacturing and service sectors, as security comes down to a price as a commodity. The vehicle design of the future will include autonomous driving, where the mapping from the position of all other actors surrounding the vehicle is a serious and delicate matter. Some of the issues discussed can be considered to evaluate future architectures. The integration of surrounding sensor positioning, maps, data, and processing has to be considered in future architectures for long-term urban interactions. The increasing predictability of speed will be matched with further requirements that are more related to cybersecurity. The potentially higher number of hacked interventions over longer timeframes may have major implications. The adoption of novel sensor technologies will also have an impact on reliability, different from isolated cases, and parallel and backup strategies will have to be considered. In this way, the present research sets the requirements for future trends in policy, road regulations, and vehicle development.

7. Conclusion

Owing to its adaptability factors particularly leading account of human-machine interaction, and machine learning-based techniques that can use various inputs to generate the vehicle outputs required to make that interaction beneficial, AI technologies hold leading status in the development of next generation AVs with higher functionality than what current road vehicle designs are able to achieve. While much research and development has taken place in this field since the early 2010s, there is still much challenging work to be undertaken in the lacking response arena, including conducting trials to get function data to develop new features and improve existing designs. Safety and regulatory compliance work is another area where in depth research is still required. Nonetheless, given the sharply increasing interest in developing enhanced vehicle capabilities to conduct freight and passenger delivery services with more competitiveness than conventional vehicles, numerous AV functionalities will benefit from speeding up developments in this area. Again, this is an area where a closer relationship within a professional knowledge exchange space could lead to next generation vehicle designs with very high adaptability factors. Work in this area would also support our empirical observation that significant interest currently exists in speeding up the process of developing measureable parameters on AV functionality. Saddling advanced AV hardware and software with outmoded functionality requirements will limit the transformative capacity of AI technologies to contribute to the future of transportation and road-use. Closing this gap will require responsible research and innovation, of the scale necessary to meaningfully engage with AI advanced technologies, focusing on the design of road vehicles with new capabilities and functionalities. Moreover to happen effectively, sociotechnical solutions that bridge the divide between these technical improvements and broader transportation systems will require multilateral conversations and the direct involvement of stakeholders, from technological innovators and futurists to regulators and transportation professionals. For those of us working to understand the specifications of a world with increasingly intelligent and adaptive road vehicles, this represents the next step.

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