# IMPROVING AUTONOMOUS VEHICLE AUTOMATION THROUGH HUMAN-SYSTEM INTERACTION


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## KEYWORDS

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## ABSTRACT

Self-driving cars (a.k.a. Autonomous Vehicles) have many challenges to tackle before having them fully deployed in our roads and cities. A critical one, which has been somehow neglected till recently, is to consider the driver in the system-user loop of vehicle performance. The purpose here is to tackle some of the current pending challenges involved in scaling up the level of autonomy of these systems. We have designed two user-vehicle experiences in two different sites with a common methodology that serves as an umbrella to collect all features required to model the driver-user. These two sites allow us to contrast and fine-tune this modelling issue. The approach consists in following a Learning Apprentice approach, where both the user behaviour and the system behaviour are learned and improved in a symbiotic ecosystem. This paper focuses on discussing the advantages of this approach and the main issues that require further research.


## INTRODUCTION

Autonomous vehicles (AV) have been available for over 34 years already (Pomerleau, 1988). However, the main question remains open, why they have not been fully deployed up to now. We argue that this is because research and developments have neglected a critical factor, the human factor. Admittedly, this factor has been largely studied regarding pedestrians (CCAM, 2021), i.e., outside the vehicle. But there is little research done on the human factor within the vehicle (Puertas-Ramirez et al., 2021). We contend that the inclusion of the driver in the system-user loop of vehicle performance is one of the key challenges to tackle before having AV fully deployed in our roads and cities.

There exists a significant gap in AV between the decisions made by the in-vehicle intelligent systems and what is needed to support autonomous functioning and better cater to user needs. This gap becomes even more challenging as the decision-making capability of the vehicle increases without considering each unique user's needs. To address this gap between the intelligent system and the driver/passenger, this work proposes a break-down methodology to reduce the gap in each case by providing a new adaptive symbiosis based on personalizing human-vehicle interaction. The goal is to increase the user's performance and satisfaction, as well as the system's level of autonomous functioning and adequacy to cater to user and context changing needs within the given situation.

Our modelling approach involves semi-supervised learning (van Engelen et al., 1992) and Learning Apprentice Systems (Dent et al.,1992), where both user-behaviour and system-behaviour are learned and modelled in a symbiotic ecosystem. Learning apprentice systems support computational models of human learning from examples and feedback. These systems have proven their applicability in a wide range of scenarios, such as Intelligence Tutoring Systems (MacLellan et al., 1992) and Calendar Apprentice Systems (Dent et al., 1992).

We explore the advantages of this approach and discuss the key issues that require further research. By incorporating the driver into the autonomous system, we aim to overcome the existing limitations and enhance the scalability of autonomous vehicle autonomy.

In our previous work (Puertas-Ramirez et al., 2021), we argued that the human driver still plays a critical role in self-driving cars by taking over the control of the vehicle if prompted. For example, drivers are required to detect and react in case of autonomous vehicle malfunctions. In autonomous vehicles, the driver's cognitive load is reduced, but the vehicle still expects the driver to maintain awareness in case of failure.

To assure safety during autonomous operation, the user state should be continuously measured, which is intended to support a "Fallback Ready State" (FRS) (Puertas-Ramirez et al., 2021). Our initial objective with this research is to measure the key elements and features involved in modelling the user-system and system-user interaction that have a real impact on user-system performance. To this we have developed the infrastructure required to deal with two real experiences of AV in two different sites and circumstances. This paves the way to define and clarify the main issues involved in a trustable user-centric methodology in autonomous vehicles.

In (Puertas-Ramirez et al., 2021) we clarified the importance of each instantaneous user-vehicle state (UVS) inside autonomous vehicles and the frontier of each human-vehicle interaction from low to high levels of automation. We argued that personalizing human-vehicle interaction is more than just managing the Take Over Requests (TORs), wherein the vehicle prompts the driver to assume control. Understanding the real behaviour of both the system and the user is the critical issue to be break-down in an adaptive symbiosis between the user and the autonomous vehicle. We must understand the bidirectional communication between them, considering that each autonomous vehicle and each individual user is a specific case in a continuous and endless interaction paradigm.

Therefore, this paper aims to achieve four objectives related to the adaptive modelling of the autonomous vehicle ecosystem based on user experiences. These objectives will advance the global objective, which is an intelligent and autonomous collaboration between the user and the system.

- **Obj. 1:** The first objective is to capture data in diverse driving scenarios where user action is essential to tailor the response of the system in a non-intrusive way for the user. This objective is critical in enabling the system to learn and adapt to different driving scenarios, ensuring that it can respond appropriately to both user actions and needs, and driving conditions supervised by the autonomous system.
- **Obj. 2:** The second objective is to create models that are adapted to each person's needs, tasks, and context, with the ability to generalise to unseen users using semi-supervised approaches to cope with the labelling bottleneck. The development of personalized models is necessary to ensure that the system can adapt to the unique driving styles and habits of each individual user, which can vary significantly depending on the person's experience, preferences, and situational context.
- **Obj. 3:** The third objective is to apply the developments in real driving environments of user-system interaction, ensuring the adequacy and adaptation of the models to changes in scenarios and over time, thus increasing the range of actions in which the system, in each context, responds autonomously. This objective is aimed at ensuring that the system can respond effectively and efficiently to changes in driving scenarios and adapt to the evolving needs and preferences of the user.
- **Obj. 4:** Finally, the fourth objective is to design indicators that facilitate the generation of a responsive framework to the person's state in various traffic contexts, thus dealing with their mental and operational factors by considering behavioural and mental-affective response variables. The development of indicators that can capture the user's mental and operational factors is essential in ensuring that the system can respond to the user's needs in a comprehensive way, considering the user's mental and emotional state, as well as their driving behaviour.

In summary, the paper aims to develop a system that can adapt to each user's needs and context while driving, with the ultimate goal of improving safety and efficiency on the road. The paper is structured into several sections, starting with a review of related work in the field, followed by a description of the proposed methodology. The configuration of the experiences in what we consider the first modelling results is then discussed, along with the evolution of autonomous vehicles and how to advance in automation levels. Finally, the paper concludes with the future work.

## RELATED WORK

To date autonomous vehicles have been successful reaching the level 5 of autonomy only in highly controlled environments where everything (excluding the user) is modelled as accurately as possible (J.Wang et al., 2021). To advance the level of autonomy in real driving conditions this methodology tackles the problem of developing a dynamic autonomous system which is able to pass through autonomy levels 3 and 4. Our working assumption is that current autonomous systems have problems in scaling up the level of autonomy because they do not take advantage of considering the human driver in the loop to adequately react to unexpected events or Take Over Requests (TORs). Currently, when something unexpected happens in SAE levels 3 and 4 (SAE-International, 2018), the vehicle must decide whether to transfer the control to the human or not. Is right here where our approach addresses the problem in a distinctive way.

In essence, we argue that to deal with that transition of control, from the system to the driver, the driver must be modelled so the autonomous system is endowed with the possibility of predicting the driver's behaviour in each situation. To collect all the required information involved, an in-depth modelling must be carried out. Our approach considers information from cameras and biometric user's data. Measuring physiological signals with non-invasive methods reliably remains a challenge. To this, there have been promising developments that propose non-contact microwave sensors to measure Heart rate and respiration (Bonyani et al., 2021). However, there is no proof to confirm that this approach is sufficiently accurate to deal with real driving conditions, which are those we are coping with in this research.

The methodology also addresses the ethics of using intelligent systems in autonomous vehicles and the importance of building trust between the user and the vehicle. The user's trust in the vehicle has often been studied (Hunter et al., 2022), (Huang et al., 2022), (Lu et al., 2023), but we argue that the autonomous system should also model how much trust it has in the user at a particular situation, in a similar way in how its own system reliability could be computed (F.Wang et al., 2022). An increased level of trust in the specific user would allow the vehicle to personalize the level of automation it provides. The open issue is how to model the user behaviour in a personalized human-vehicle interaction based on the user's experiences in dealing with the autonomous system in real driving conditions.

To achieve the aforementioned objectives with an approach that tries to avoid bias derived from dealing with certain experimentation conditions, we collect data in two driving scenarios where user action is essential to tailor the response of the system in a non-intrusive way for the user. This data is used to create models adapted to each person's needs-tasks-context with the ability to generalise to unseen users using semi-supervised approaches to cope with the labelling bottleneck. This work entails applying the developed models in real driving environments of formal user-system interaction, ensuring the adequacy and adaptation of the models to changes in scenarios and over time, thus increasing the range of actions in which the system responds autonomously. Design indicators are obtained to facilitate the generation of a responsive framework to the person's state in various traffic contexts, dealing with their mental and operational factors by considering behavioural and mental-affective response variables. The methodology includes a discussion on the evolution of autonomous vehicles and how to advance in automation levels. Finally, the study concludes with a presentation of the conclusions and future work.

## METHODOLOGY

An innovative methodology, which integrates a multi-sensor approach with semi-supervised machine learning techniques, has been implemented across two driving scenarios. This methodology offers precise human-centric and on-board environment information for future driverless vehicles. In this methodology, real-world driving data is continuously collected from the driver/user in autonomous vehicles circulating at University of West of Scotland (UWS) and University Carlos III of Madrid (UC3M). This innovative approach allows for an in-depth comparison of devices, various driving conditions and level of automation, supporting a detailed assessment on when, why, and how the driver may handle Take Over Requests (TORs) in autonomous vehicles to increase their level of automation.

In our methodology, real driving data is used to provide a more authentic experience for the driver/user in an autonomous vehicle. Figure 1 provides a summary of the key issues addressed in each stage of the proposed methodology applied to both driving scenarios at UWS and UC3M. This approach overcomes the limitations (Risto et al., 2014) of most common studies that rely on simulators (Hunter et al., 2022).

The first scenario at UWS consists of a Toyota Prius PHEV driven in real-world traffic situations with a Level 2 of autonomy and equipped with Adaptive Cruise Control (ACC), Automated Lane Centering (ALC), Forward Collision Warning (FCW), and Lane Departure Warning (LDW) systems. The autonomous functionality is achieved using OpenPilot software (Comma-ai-inc, 2022), which overrides the vehicle's original CAN messages and utilises custom CAN messages to control the actuators such as the steering wheel, brake, and throttle.

The second scenario takes place at UC3M and consists of an autonomous vehicle prototype with level 5 automation, named iCab (Intelligent Campus AutomoBile) (Marin-Plaza et al., 2019), which is driven in a campus-site situation, where there is an outdoor environment with pedestrians. This prototype is based on an electric golf cart, and the steering wheel has been removed to provide users with a genuine experience of a fully autonomous vehicle. In this scenario, the user can only activate the brake in case of an emergency. A linear motor actuator has been incorporated to apply friction and decelerate the autonomous vehicle. The software for managing the fully autonomous mode is based on ROS2 (Robot Operating System 2) (Stanford Artificial Intelligence Laboratory et al, 2023) to ensure real-time connection and synchronisation among sensors.

The core of this methodology is centred around algorithms that focus on human active modelling. Models adapted to each person's needs-tasks-contexts are created using semi-supervised learning approaches to cope with the labelling bottleneck. These models need to utilise data from various sensing devices, which are continuously measuring the driver/user's state to ensure a "Fallback Ready State" (FRS). Furthermore, driving scenarios require active engagement, attention, and awareness from the user to detect and respond to real situations such as Take Over Requests (TORs) and system failures like brake malfunctions.

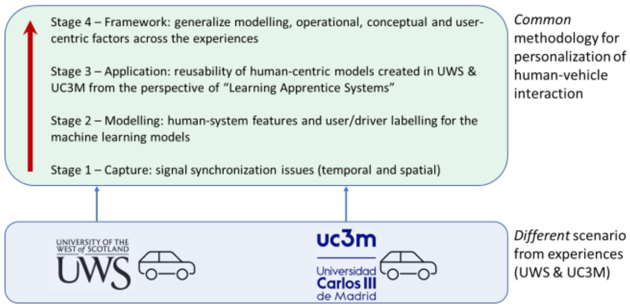


*Figure 1 Overall concept of the methodology applied at UWS & UC3M*

## CONFIGURATION OF THE EXPERIENCES

### Experimentation Dataset from UWS

A series of experiments were conducted to assess the driver's state of awareness and their TORs in autonomous vehicles. These experiments aimed to compare the driver's reactions with those of the autonomous system. Multiple data sources were utilised to gather comprehensive information:

**Visual Data:** Two cameras were employed to capture RGB information, depth field of view, and Infra-Red (IR) imagery.

**Physiological Data:** An Empatica E4 wristband was worn by the driver to monitor various physiological signals, including pulse, skin conductance (EDA), skin temperature, breath rate, heart rate, accelerometer, and gyroscope.

**Driver Behaviour Analysis:** The Intel RealSense d435i camera was utilised to analyse the driver's full body and detect any movements or external influences, such as using a mobile device on the driver's lap.

The experiments consisted of 16 consecutive scenarios specifically designed to assess the driver's state of awareness. Each scenario was compared against the reactions and warnings generated by the autonomous driving system. Prior to each series of experiences, a baseline measurement of the driver's physiological signals in a normal, calm, and relaxed state was taken. This baseline was obtained by measuring the signals during a 3-minute rest period before and after the series of experiences.

The scenarios that have been conducted so far are as follows:

(1) Lane Change: Head turned to the opposite side with hands on the steering wheel.

(2) Lane Change: Head turned to the opposite side without hands on the steering wheel.

(3) Head Up: Looking upwards, raising the head, and focusing on the road with hands on the steering wheel.

(4) Head Up: Looking upwards, raising the head, and focusing on the road without hands on the steering wheel.

(5) Head Up: Looking upwards, raising the head, without focusing on the road with hands on the steering wheel.
(6) Head Up: Looking upwards, raising the head, without focusing on the road and without hands on the steering wheel.
(7) Head Down: Lowering the head while still looking at the road with hands on the steering wheel.
(8) Head Down: Lowering the head while still looking at the road without hands on the steering wheel.
(9) Head Down: Lowering the head without looking at the road with hands on the steering wheel.
(10) Head Down: Lowering the head without looking at the road and without hands on the steering wheel.
(11) Looking Road but Inattentive: Not actively observing the surroundings, with hands on the steering wheel.
(12) Looking Road but Inattentive: Not actively observing the surroundings without hands on the steering wheel.
(13) Reaction to Sudden Startle: Immediate response to unexpected events (e.g., noise, bump, flat tire) while inattentive, with hands on the steering wheel.
(14) Reaction to Sudden Startle: Immediate response to unexpected events (e.g., noise, bump, flat tire) while inattentive, without hands on the steering wheel.
(15) Reaction to Sudden Startle: Immediate response to unexpected events (e.g., noise, bump, flat tire) when in a state of awareness with hands on the steering wheel.
(16) Reaction to Sudden Startle: Immediate response to unexpected events (e.g., noise, bump, flat tire) when in a state of awareness without hands on the steering wheel.

Figure 2 shows a snapshot of some of the images recorded from the different cameras mentioned above, internal, and external, in the UWS autonomous vehicle in real driving conditions (Toyota Prius)

*Figure 2 Snapshot of human centred AV recording at UWS. From left to right: intel RealSense (Colour), OpenPilot (Interior), OpenPilot (Exterior)*

**Experimentation Dataset from UC3M**

In the UC3M setting, we conducted our experiments using the iCab vehicle (Marin-Plaza et al., 2019), which is a level 5 autonomous vehicle experimental platform. The iCab vehicle allows the "driver" to intervene and stop the vehicle in the event of an unexpected occurrence. To monitor the driver's behaviour, we designed a perception system that operates independently of the autonomous vehicle navigation system.
The driver's perception system comprises three cameras: the Intel RealSense d435 (for analysing the full body of the driver), the Webcam Logitech Brio 4K (for detecting facial expressions), and the OAK-1 (for perceiving the front of the vehicle). Currently, we are collecting data from wearable devices to measure biometric data. The primary objective at this stage is to investigate whether physiological signals are truly necessary. Ultimately, we aim to provide a non-intrusive or minimally intrusive solution.
Unlike the UWS public road environment, the UC3M experiments were conducted on public pedestrian streets within the university grounds. These streets allow for low vehicle speeds, thereby reducing the risk of collision-related damages. Our experimentation circuit is located within the UC3M "Escuela Politécnica Superior" campus, which has been fully modelled as part of previous research on fully automated taxi transport (Marin-Plaza et al., 2019). Depending on the level of pedestrian activity, the entire trajectory takes approximately 10-15 minutes. The presence of pedestrians and maintenance vehicles on the same path exposes us to frequent unexpected events. This setup enables us to observe how users react to real-life situations that may occur in other environments, providing a wide range of circumstances and valuable lessons.
At the beginning and end of each series of scenarios within a given experimentation set, we measure the baseline user state. In some scenarios, the user performs specific tasks to simulate a Cognitive Distracted User. The scenarios being conducted in this study include:
(1) Relaxed Drive through the whole circuit.
(2) Reaction to a pedestrian walking straight at the vehicle.
(3) Reaction to a pedestrian crossing with good visibility.
(4) Reaction to a pedestrian crossing with poor visibility (requiring low reaction time).
(5) Cognitive Distracted User: Reaction to a pedestrian walking straight at the vehicle.
(6) Cognitive Distracted User: Reaction to a pedestrian crossing with good visibility.
(7) Cognitive Distracted User: Reaction to a pedestrian crossing with poor visibility (requiring low reaction time).
(8) Planned Automation Failure Drive: No warning.
(9) Planned Automation Failure Drive: Cognitive Distracted User, no warning.

Please note that additional scenarios may be included in future iterations of our experiments to further explore various aspects of autonomous driving and driver behaviour.

Figure 3 shows a snapshot of some of the images recorded from the different cameras mentioned above in the UC3M autonomous vehicle in real driving conditions (iCAB)

*Figure 3 Snapshot of human centred AV recording at UC3M: Top-left corner: Intel RealSense (infrared stream), Lower-left corner: Intel RealSense (depth stream), Top-right corner: Intel RealSense (colour stream), Lower-right corner (filtered colour stream)*

## HUMAN-CENTRIC SYMBIOTIC ARTIFICIAL INTELLIGENCE

Our proposal is framed, among other AI related research, in the field of symbiotic interactions between humans and intelligent machines. Human-centric symbiotic artificial intelligence (HCSAI) refers to the design and development of AI systems that prioritise collaboration, cooperation, and mutual enhancement between humans and AI agents (O'Neill et al., 2023). In this section, we explore the concept of HCSAI, its underlying principles, and its potential impact on various domains.

Understanding Human-Centric Symbiosis: At the core of HCSAI is the notion that AI systems should be designed to augment human capabilities, rather than replace or subjugate them. This symbiotic relationship emphasises the importance of collaboration and cooperation between humans and AI agents, with the goal of enhancing human decision-making, problem-solving, and overall well-being. By integrating AI technologies into human-centred systems, HCSAI aims to create an environment where humans and AI agents work together seamlessly, leveraging each other's strengths and compensating for their respective weaknesses.

Key Principles of HCSAI:

1. Mutual Empowerment: HCSAI focuses on empowering both humans and AI agents, enabling them to leverage their unique strengths to accomplish shared goals (Abedin et al., 2022). This principle emphasises the need for AI systems to enhance human capabilities rather than overshadow them, fostering a sense of agency and control for humans while leveraging AI's computational power.
2. Transparency and Explainability: To establish trust and effective collaboration, HCSAI systems should provide transparent explanations of their reasoning and decision-making processes. Human users should have a clear understanding of how the AI agent operates and how it arrives at its conclusions. This transparency not only fosters trust but also allows humans to provide feedback, correct biases, and make informed decisions based on AI-generated insights (Datta et al., 2016).
3. Adaptability and Context-Awareness: HCSAI systems should be adaptable to dynamic human needs and contexts. They should be able to learn and understand human preferences, adapt their behaviour accordingly, and proactively assist humans in achieving their goals. Context-awareness enables AI agents to interpret and respond appropriately to human emotions, intentions, and situational cues, facilitating more natural and effective interactions (Hasanov et al., 2019).
4. Ethical Considerations: HCSAI puts a strong emphasis on ethical design and responsible AI deployment. Human well-being, privacy, fairness, and social impact should be prioritised in the development of HCSAI systems. Ethical considerations include addressing biases, ensuring transparency, protecting privacy, and mitigating potential negative consequences of AI-enabled decision-making (Jobin et al., 2019).

Potential Applications of HCSAI: HCSAI has the potential to revolutionise various domains by augmenting human capabilities and enabling new modes of collaboration. Some potential application areas include:

1. Healthcare: HCSAI can assist healthcare professionals in diagnosis, treatment planning, and patient monitoring. It can provide intelligent decision support, analyse vast amounts of medical data, and enhance patient-doctor communication (Waring et al., 2020).
2. Education: HCSAI can support personalised learning experiences, adapt instructional content to individual needs, and provide intelligent tutoring systems that enhance student engagement and knowledge acquisition (Wayne et al., 2023).
3. Smart Assistants: HCSAI can power intelligent virtual assistants that anticipate user needs, provide personalized recommendations, and assist with everyday tasks, improving productivity and convenience (Cila, 2022).
4. Social Robotics: HCSAI can enable the development of socially intelligent robots that can understand and respond to human emotions, facilitate social interactions, and provide companionship for the elderly or individuals with special needs (Blut et al., 2021).
5. Communities for Health and Independent Living: This topic was the target of the Project CISVI (TSI-020301-2008-21), which focused on fostering the inclusion into the society of people with cognitive and physical disabilities (Barrera et al., 2009). Empowering people with disabilities to meet the challenges for their independent life in terms of the new AI technologies is a pending issue that deserves further research and development. Research in Advanced Learning Technologies (ALT) could have a direct impact on the improvement of the quality of life (QoL) of disabled and non-disabled people. QoL represents the degree to which an individual can establish and sustain a viable self in the social world (Brown, 2003). However, technology is very often not ready to support the final user in this way.

Conclusion: Human-centric symbiotic artificial intelligence represents a paradigm shift in AI design, prioritising the collaboration and cooperation between humans and AI agents. By adhering to principles such as mutual empowerment, transparency, adaptability, and ethical considerations, HCSAI systems can create synergistic relationships that amplify human abilities while addressing societal challenges. The potential applications of HCSAI are vast and span various domains, promising a future where humans and AI agents work together harmoniously to achieve shared goals and improve the human experience.

## CONCLUSIONS AND FUTURE WORK

In this paper, we presented an innovative, human-centric modelling strategy designed to elevate vehicle autonomy. Our approach merges multi-sensor data collection with semi-supervised machine learning algorithms, all centred around gauging the driver's state within autonomous vehicles. We achieve this by fostering a symbiotic relationship between the performance capabilities of both the human driver and the autonomous system, thereby enhancing responses to high-risk scenarios. This approach entails personalizing the user-vehicle interaction, where users/drivers need to be modelled while safely interacting with vehicles in different real driving circumstances, thereby fostering increased trust between the user/driver and the intelligent autonomous system. Our argument is that focusing on user-system and system-user learning through specific, individualised, and unique modelling is essential to enhance the performance of automatic systems. Such systems will then be capable of recommending accurate actions to manage sudden and ever-changing difficulties that can arise in real-world situations, such as traffic scenarios.

To observe and monitor the driver/user and their interaction with the autonomous vehicle, we propose collecting multimodal data through computer vision and wearable devices, which in our experimentation are integrated into two different autonomous vehicles, as described in the UWS and UC3M sections. This approach gives us the advantage of being able to determine, from a methodological point of view, which distinctive features have value in different events and contexts and which circumstances are more or less difficult to ascertain. In this way, we can weigh the true value of a particular sensor and characteristic in each situation and context.

The ultimate goal is to gradually achieve higher levels of autonomy, potentially reaching level 5 (fully autonomous) based on the ongoing experimentation. These experiences are currently in progress, and we expect them to demonstrate the potential of the proposed methodology in improving the interaction between drivers/users and systems, thereby addressing some of the existing challenges in increasing the autonomy of future autonomous vehicle systems.

In addition, starting from a semi-supervised approach we are exploring various machine learning techniques that can be used within a generic framework to learn how to create the ecosystem that we are devising here, where the symbiosis of collaboration between the user and the autonomous system can improve the performance of the final result, unique to the entire system. It is important to note that the generality of this framework is not solely supported by the experimentation presented in this paper. This modelling approach is already being implemented as part of a coordinated research project (HUManAId, ref: TED2021-129485B-C4), which encompasses three additional real-life scenarios that require user interaction with an intelligent system. We contend that to facilitate and expedite the adoption of intelligent systems in our daily lives, personalization is crucial, as it fosters mutual understanding and trust between the user-system and system-user.

In future work, we plan to continue refining our modelling approach and conducting experiments in various scenarios to further validate its effectiveness. Additionally, we will explore additional machine learning techniques and frameworks to enhance the performance and adaptability of autonomous systems. By addressing the challenges and leveraging the insights gained from our research, we aim to accelerate the integration of intelligent systems into society while ensuring a safe and trustworthy user experience.

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