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Human-Robot Interaction in Autonomous Vehicles

Addressing Trust, Safety, and Cognitive Load Challenges

Final Individual Research Project
Big Data, IoT & the Cloud

University of Nebraska at Omaha

Abstract

The integration of autonomous vehicles into transportation systems presents challenges in human-robot interaction, particularly regarding trust calibration and cognitive load management. This paper examines the relationship between human users and autonomous vehicles through four key research questions: factors influencing trust in AVs, indicators of effective trust calibration, cognitive load impacts on decision-making, and existing gaps in human-robot interactions. Through analysis of current research, findings reveal that trust in AVs is primarily influenced by emotional factors and system performance rather than technical knowledge. The study identifies indicators for assessing trust calibration, while demonstrating how cognitive load affects user decision-making. The paper concludes that successful AV integration requires a balanced approach combining trust calibration mechanisms with user-centered design principles to create systems that are both technologically advanced and inherently trustworthy.

Introduction

The rise of autonomous vehicles marks a significant shift in the role of technology within the transportation industry. As shown by current market trends, the automotive industry is rapidly moving towards higher levels of autonomy, with Level 2 and Level 3 autonomous features expected to reach 33% of newly registered cars worldwide by 2028. This change brings both exciting possibilities and new challenges for the world, especially in how people will interact with these automated vehicles. Waymo, for example, is already running self-driving taxis in San Francisco, Phoenix, Los Angeles, and Austin, with over 150,000 rides per week (Road to Autonomy, 2024). This figure is only one indicator that autonomous driving is a technology that is becoming a part of everyday life for many people. However, this rapid progress raises questions that cannot be overlooked. How do people adapt to sharing the road with self-driving vehicles? How comfortable do people feel letting a robot take the wheel? What are the factors that influence and determine the answers to these questions? The answer to these questions does not simply lie in developing better technology. Rather, the answer lies in understanding how people feel about and adapt to these changes, thus the need to make sure autonomous driving systems are designed with human needs and human behavior in mind. The successful integration of self-driving cars into society depends not just on the technology itself, but on how well we can integrate them into our daily lives.

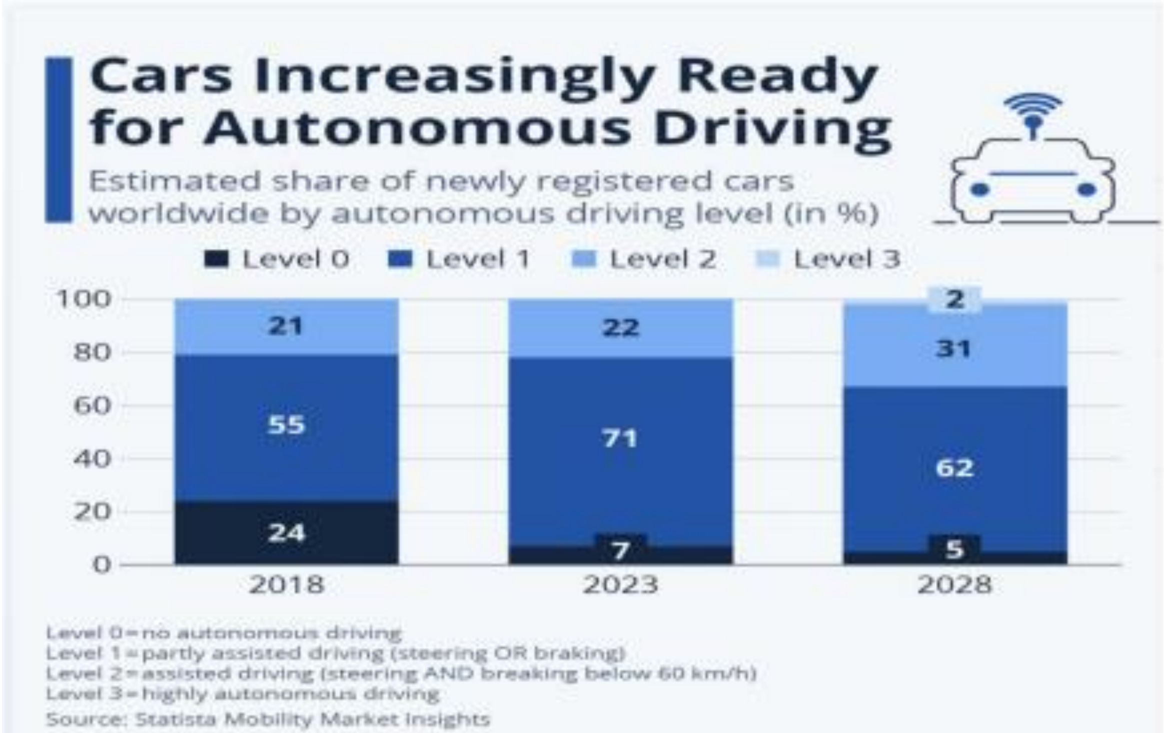


Figure 1: Estimated share of newly registered cars worldwide by autonomous driving level from 2018 to 2028 (Statista Mobility Market Insights, 2024)

While autonomous vehicles are touted for their potential to reduce human error, certain risks arise from potential failures in the technical and decision-making components of these vehicles, particularly when human intervention becomes necessary. The IoT infrastructure supporting autonomous vehicles adds another layer of complexity to these considerations, as it involves the exchange of vast amounts of data between vehicles, infrastructure, and other connected devices.

Cognitive load plays a vital role in human interaction with autonomous vehicles, as these machines rely on advanced sensors, machine learning algorithms, and artificial intelligence to interpret their surroundings. These vehicles must simultaneously communicate with other Internet of Things (IoT) devices and systems, interact with other road users, and interpret laws and non-automated road signs.

Humans must process the information provided by AVs, which can be overwhelming if not properly managed. Poorly designed interfaces, for example, or an overabundance of unnecessary data can lead to confusion, reduced situational awareness, and ultimately, diminished safety or a sense of diminished safety for the user. Striking a balance between providing relevant information to the user and ensuring a user-friendly interaction with autonomous vehicles is one key to the success of autonomous driving endeavors. As autonomous vehicles continue to evolve, our understanding of the dynamics between human users and these interconnected systems must also follow a similar trajectory. This paper will examine and investigate these dynamics and emphasize the importance of user-centered design in the development of autonomous vehicles.

Research Questions

1. What are the primary factors that influence human trust in autonomous vehicles?
2. What measurable and immeasurable indicators demonstrate effective trust calibration in human-robot interactions with autonomous vehicles?
3. In what ways does cognitive load influence user decision-making and what design features can alleviate cognitive overload to enhance user experience?
4. What gaps exist in the industry regarding human-robot interactions in autonomous vehicles, and how can future research and developments address these gaps?

Methodology

This paper will use a review of the relevant literature, focusing on the key areas such as HRI in autonomous systems, human trust in automation, safety frameworks in autonomous vehicles, and cognitive load challenges in human-robot interaction. The literature review will consist of, but not be limited to, peer-reviewed journals, conference proceedings, and industry reports. The aim of the literature review is to identify models that explain safety, human trust, and cognitive load in human-robot interaction, identify existing findings on how humans interact with autonomous vehicles, and identify knowledge gaps in the literature. Academic databases such as IEEE Xplore and Google Scholar will be consulted. The literature review will also focus on studies published within the last seven years. In addition to the literature review, this paper will graphical and visualization analysis as well as from various sources.

1. Primary Factors Influencing Human Trust in Autonomous Vehicles

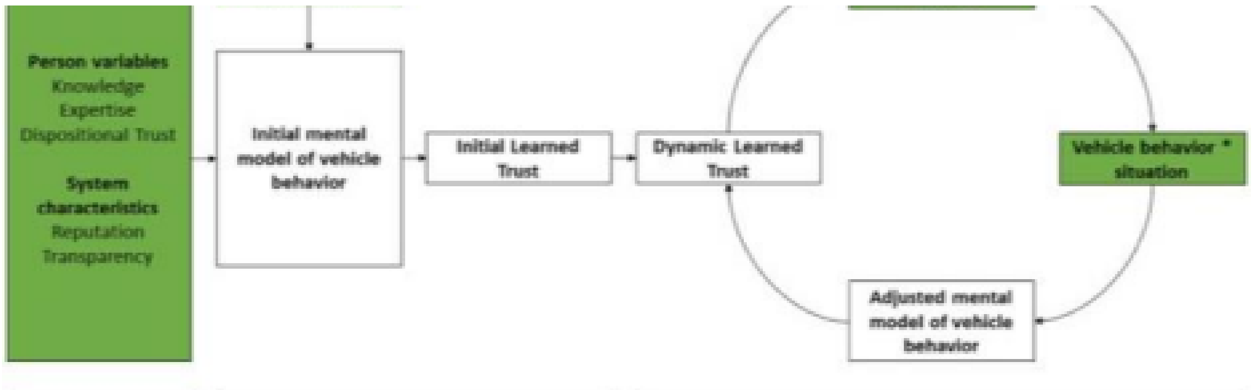


Figure 2: Process of how human trust in automated vehicle systems develops

The diagram above presents a comprehensive model of trust development in automated vehicle systems through an interconnected process (Kraus et al., 2020, Figure 1). It begins with two-person variables such as knowledge, expertise, and dispositional trust, and system characteristics comprising reputation and transparency. These elements combine to form an initial mental model of vehicle behavior, which then evolves into Initial Learned Trust. As users interact with the vehicle, this initial trust transforms into Dynamic Learned Trust, which continuously adapts through a feedback loop. The cycle shows how vehicle behavior in various situations influences the adjusted mental model, which in turn affects the Dynamic Learned Trust—how user trust level or perception changes based on their experience with AVS. This creates an ongoing learning process where trust is constantly calibrated based on real-world experiences and interactions with the automated vehicle system. The green highlighting of the input variables and output behavior emphasizes the key starting and endpoint elements of this trust development cycle, illustrating how trust in automated vehicles is not static but rather an evolving relationship between user and system.

Trust calibration in AVs is a dynamic process that evolves as users gain more experience with these systems. It involves the continuous adjustment of trust levels based on system performance, user experiences, and the range of encountered situations within the IoT-enabled transportation network (Wagner et al., 2023). Simultaneously, it is important that users develop appropriate levels of trust that match the actual capabilities of the AV system. The integration of autonomous vehicles (AVs) into the Internet of Things (IoT) ecosystem has brought forth a complex interplay of factors that influence human trust in these systems. The successful deployment and adoption of AVs within the broader context of smart transportation networks relies heavily on understanding these factors. Research indicates that the level of trust in an autonomous vehicle is more significantly influenced by the range and quality of situations it successfully navigates rather than the mere distance it travels (Beggiato et al., 2015; Wagner et al., 2023). This finding emphasizes the importance of AVs demonstrating adaptability and reliability across diverse real-life contexts within the IoT-enabled transportation infrastructure. Interestingly, while high reliability in autonomous vehicles generally improves user trust and performance, the relationship remains complex. Excessive trust in highly reliable systems can lead to dangerous over-reliance, particularly in scenarios where human intervention is sometimes necessary for safety. Thus, a delicate balance must be struck to maintain user vigilance and prevent overconfidence (Wagner et al., 2023).

System performance and reliability emerge as two intertwined factors that significantly influence human trust in AVs. Vehicles must not only possess strong situational awareness but also clearly communicate their "intent" and actions (Feng & Kim, 2018). For instance, providing auditory feedback to indicate pedestrian detection can build trust by demonstrating the vehicle's level of awareness within the IoT-connected environment. Furthermore, the ability of an AV to model human behavior while accommodating the needs and desires of the human user is crucial. The vehicle should operate in a manner that feels natural and predictable to human passengers and other road users, adhering to traffic rules much like a competent human driver would (Feng & Kim, 2018).

An interesting aspect of trust in AVs is that it is determined more by emotional factors than by knowledge about the technology (Robinson-Tay & Peng, 2024). Research consistently shows that human exposure to AVs plays a significant role in trust calibration, with trust typically increasing rapidly after initial exposure and then stabilizing with increased exposure (Wagner et al., 2023). This suggests that emotional comfort is a considerable factor in developing trust in autonomous vehicles within the IoT ecosystem. Individual differences in personality and emotional states also play a role, with factors such as self-esteem, self-efficacy, and state anxiety significantly predicting trust in automated systems (Wagner, 2023).

The concept of trust recovery after system malfunctions or errors has also gained attention in the context of IoT-enabled AVs. The ability of users to regain trust following a system failure, and the AV's capacity to demonstrate error recovery, are integral components of long-term trust calibration (Wagner et al., 2023). This highlights the importance of designing AVs that not only perform well under normal conditions but also handle unexpected situations effectively within the complex IoT environment. As autonomous vehicles continue to evolve and become more integrated into the IoT ecosystem, understanding and addressing these trust factors will be crucial for their successful deployment and adoption. The interplay between human trust, AV capabilities, and the broader IoT infrastructure presents both challenges and opportunities for researchers and developers in the field of autonomous transportation.

2. **What Measurable and Immeasurable Indicators Demonstrate Effective Trust Calibration in Human-Robot Interactions with Autonomous Vehicles?**

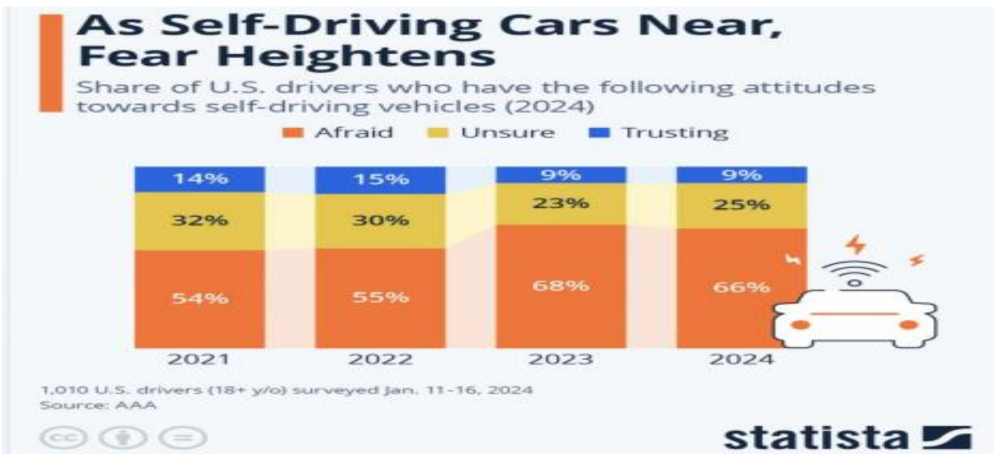


Figure 3: U.S. Driver Attitudes Toward Self-Driving Cars

As shown in the above graph, the percentage of U.S. drivers who have a fear of self-driving vehicles has increased from 54% in 2021 to 66% in 2024 (AAA, 2024). Trust in AVs has declined from 14% in 2021 to 9% in 2024, while the proportion of drivers who feel unsure about AVs has remained relatively stable, around 25%. This graph illustrates a significant trust gap that needs to be addressed for successful AV integration into daily transportation. Trust calibration, as a concept in human-autonomous vehicle (AV) interactions, is a complex process that involves both measurable and immeasurable indicators, providing insights into how well user-trust aligns with the actual capabilities of the AV system. To comprehensively assess trust calibration, researchers employ a combination of subjective and objective measures, each offering unique perspectives on the user's relationship with the AV.

Measurable indicators of effective trust calibration include response times and takeover performance when disengaging automation, as well as the accuracy of user decision-making during critical situations (Wagner et al., 2023). In AVs, these metrics can be precisely tracked and analyzed through integrated sensors and data processing systems, allowing for real-time monitoring and assessment of user trust levels. The frequency and appropriateness of human interventions serve as another quantifiable indicator, offering a comprehensive view of trust calibration over time and across various scenarios.

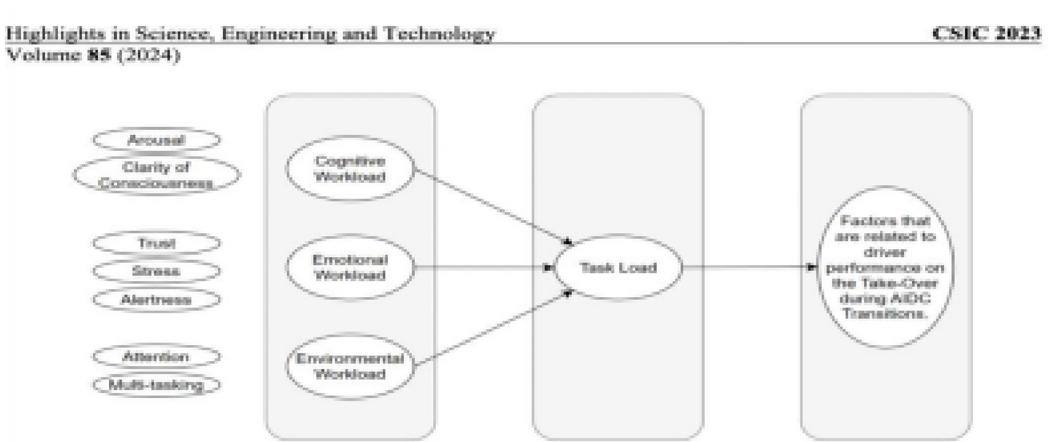
Complementing these measurable indicators are immeasurable factors that, while challenging to quantify, are equally important in understanding trust calibration. User confidence in the system's capabilities can be inferred from behavioral patterns and interaction styles with the AV interface. Appropriate levels of situational awareness, though difficult to measure directly, can be assessed through eye-tracking technologies and other IoT-enabled monitoring systems. Emotional comfort when using the AV, while not directly measurable, may be indirectly assessed through advances in affective computing and IoT sensor technologies that analyze physiological signals and facial expressions (Feng & Kim, 2018).

Subjective measures, such as self-report questionnaires and interviews, play a crucial role in capturing users' perceptions, beliefs, and attitudes towards AV systems. The Trust in Automation scale (Jian et al., 2000), adapted for AV contexts (Beggiato et al., 2015), assesses various dimensions of trust, including perceived reliability, competence, and predictability. These subjective measures can be administered at different points during AV interactions to track changes in trust over time and across situations. Objective measures focus on observable behaviors and physiological responses, including eye-tracking data, electrodermal activity, and performance metrics such as reaction times and error rates during takeover situations. These measures can be continuously collected and analyzed in real-time, providing a dynamic picture of trust calibration throughout the user's interaction with the AV.

A promising approach in trust calibration assessment is the use of behavioral indicators as proxies for trust. Okamura and Yamada (2020) proposed a framework for adaptive trust calibration that analyzes observable choice behavior to estimate trust calibration status. This method monitors user behavior in real-time, observing how drivers interact with the vehicle's autonomous features to infer whether their trust is appropriately calibrated to the AV's capabilities (Wagner et al., 2023). By correlating various behavioral patterns, such as gaze patterns or stress levels, with choice behaviors, researchers can gain a more comprehensive picture of the driver's trust state (Sanghavi, 2020). The adaptive nature of this approach is particularly valuable in the context of AVs, as it potentially reduces cognitive load on the driver by intervening only when necessary. Moreover, the framework's ability to detect both over-trust and under-trust allows for a nuanced approach to trust calibration (Wagner et al., 2023). By integrating contextual data such as traffic conditions, weather, and road characteristics, researchers can provide a more detailed understanding of how trust calibration varies across different driving scenarios.

It is important to note that effective trust calibration is not about maximizing trust, but rather achieving an appropriate balance between trust and the automation's capabilities. For instance, drivers preparing to resume control when they anticipate the AV issuing a request to intervene might indicate good trust calibration (Wagner et al., 2023). By combining subjective and objective measures within this framework, researchers and developers can gain a comprehensive view of trust calibration, capturing not only the user's stated trust levels but also their actual behaviors and physiological responses. This multifaceted approach provides a more accurate and holistic assessment of trust calibration in human-AV interactions, ultimately contributing to the development of more trustworthy and effective autonomous vehicle systems.

3. In What Ways Does Cognitive Load Influence User Decision-Making and What Design Features Can Alleviate Cognitive Overload to Enhance User Experience?



This diagram from Highlights in Science, Engineering and Technology presents a comprehensive model of driver performance during AIDC (Automated/Intelligent Driver Control) transitions (Liu & Zhang, 2024). The model begins with seven factors—arousal, clarity of consciousness, trust, stress, alertness, attention, and multi-tasking. These factors feed into three distinct workload categories—cognitive workload, emotional workload, and environmental workload. These workload types collectively determine the overall task load, as indicated by connecting arrows. The task load, in turn, directly influences the factors related to driver performance during take-over situations in AIDC transitions, the final outcome on the right side of the diagram. This diagram illustrates how various psychological, cognitive, and environmental factors ultimately impact a driver's ability to handle automated driving system transitions.

Cognitive load significantly influences user decision-making in interactions with autonomous vehicles (AVs). High cognitive load can impair takeover performance, resulting in longer response times and decreased accuracy when drivers are required to regain control of the vehicle (Wagner, 2023). Additionally, rapid transitions between varying levels of cognitive load can further complicate decision-making processes, as users may struggle to adapt quickly to changing demands. Thus, managing cognitive load effectively is essential to enhancing user experience and safety during AV operation.

To achieve efficiency in balancing cognitive overload and improving user experience, certain design features can be implemented. One effective strategy is the combination of auditory and visual information to convey critical messages. Research indicates that such an approach can enhance driving performance while simultaneously reducing cognitive load (Oppelt et al., 2024). The autonomous vehicle's provision of information through multiple channels allows users to better process and understand essential driving cues without becoming overwhelmed.

Another promising design feature is task sharing, where smart systems handle specific aspects of driving—such as longitudinal control—while allowing the human driver to maintain engagement with the vehicle. This collaborative approach keeps users prepared to take control if necessary, thereby improving the user's overall readiness and reducing cognitive strain (Singh, 2016).

That the AV can issue efficient and appropriate instructions is important for effective human-machine interface (HMI) design. Communications that instruct users without overwhelming them with excessive information help support the user in better decision-making (Oppelt et al., 2024). Aligning information presentation with human learning and cognitive processes is another vital consideration; when information is structured in a way that matches how humans naturally process and learn, it enhances understanding and usability while minimizing cognitive overload (Oppelt et al., 2024). Minimizing perceptual and informational load, which involves reducing unnecessary visual and auditory stimuli that may distract users from critical tasks, can prevent cognitive overload.

4. **What Gaps Exist in The Industry Regarding Human-Robot Interactions in Autonomous Vehicles, and How Can Future Research and Developments Address These Gaps?** Despite significant advancements in autonomous vehicle (AV) technology, several gaps remain in our understanding of human-robot interactions within the world of AVs. One critical area for improvement is bridging the reality gap between simulated environments and real-world scenarios. While simulations provide valuable insights, they often fail to capture the full complexity of real-world interactions. Developing more accurate and immersive virtual reality experiences could help address this gap and allow researchers to study human-AV interactions in a controlled, yet realistic environment (Park, 2024).

Recent research from the University of California Irvine and Japan's Keio University have uncovered significant vulnerabilities in lidar systems used by autonomous vehicles, highlighting critical gaps in human-robot interactions and vehicle security (Sato et al., 2024). One major gap exposed by this research is the potential for malicious attacks on autonomous vehicles' perception systems. The ability to spoof lidar systems, either by creating false object detections or blocking real object detection, reveals a critical vulnerability in the current state of AV technology (White, 2024). This gap in security could impact the trust between humans and autonomous vehicles, a determining factor in the widespread adoption of AVs.

Another industry gap highlighted by this research is the need for more robust and resilient sensing technologies. While newer generation lidar systems have shown improved resistance to some types of attacks, the study emphasizes the importance of further enhancing these systems (Chen et al., 2024). This points to a gap in the development of sensing technologies that can withstand various forms of interference or manipulation. The research also exposes a gap in the redundancy of autonomous vehicle systems. The suggestion to implement additional redundancy in sensing technologies (Sato et al., 2024) indicates that current systems may not have sufficient backup measures to ensure safety in case of sensor failure or manipulation. These findings connect directly to broader gaps in human-robot interaction within the AV industry. The potential for unpredictable and dangerous driving behavior resulting from lidar vulnerabilities could erode public trust in autonomous vehicles. This trust gap is a barrier to the widespread acceptance and adoption of AVs.

Another gap in the industry is addressing individual differences in human-AV interactions. Factors such as age, technological familiarity, life experiences, and personality traits can significantly impact how individuals interact with and trust AVs. Wagner et al. (2023) noted that factors like self-esteem, self-efficacy, and state anxiety predict trust in automated systems. There is definitely space for the consideration of how individual differences can be personalized and be developed for the sake of more effective AV interfaces. The development of effective external Human-Machine Interfaces (eHMIs) is another area in the industry that requires attention. User interfaces are one of the most essential elements for communicating AV intentions to pedestrians and other road users. Future research could focus on creating universally understood visual and auditory cues that can effectively convey an AV's intended actions in various traffic scenarios (Park, 2024).

Maintaining appropriate levels of situational awareness in AV users, especially during prolonged periods of autonomous operation, remains a significant challenge. Keeping humans engaged when they have little to do is virtually impossible (Sheridan, 1995), therefore, research is needed to develop strategies that keep users appropriately engaged and ready to take control when necessary, without causing cognitive overload or fatigue. Interdisciplinary approaches that combine insights from psychology, human factors, computer science, and engineering can help bridge these gaps. The framework proposed by Okamura and Yamada (2020) for adaptive trust calibration offers a promising direction, using behavioral indicators as proxies for trust. This approach could be expanded to incorporate more diverse indicators and adapted for long-term studies. Additionally, as AVs become more advanced, developing adaptive interfaces that adjust based on real-time data about the user's trust levels and the vehicle's performance in various environments. Addressing these gaps will require collaborative efforts across disciplines and a commitment to long-term, real-world studies. By focusing on these areas, researchers and developers can work towards creating AVs that are not only technologically advanced but also capable of fostering appropriate levels of trust and effective interactions with human users.

Conclusion

As autonomous vehicles continue to evolve, addressing the fundamental challenges of trust calibration, safety enhancement, and cognitive load management in human-robot interaction becomes an increasing need. The identified gaps in bridging simulation-to-reality transitions, understanding individual differences, and developing effective human-machine interfaces present crucial opportunities for advancement. Future partially relies on these human factors alongside technological capabilities, particularly through adaptive interface design and real-time trust monitoring systems.

The successful deployment and integration of autonomous vehicles into our transportation infrastructure will depend on creating systems that are both technologically sophisticated and inherently trustworthy. Adopting an integrated approach that combines trust calibration mechanisms, cognitive load optimization, and user-centered design principles can propel the AV industry into seamless integration into daily transportation systems, which would in turn create a transportation future that is not only more efficient and accessible but also fundamentally safer for AV users, pedestrians, and other road users.

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