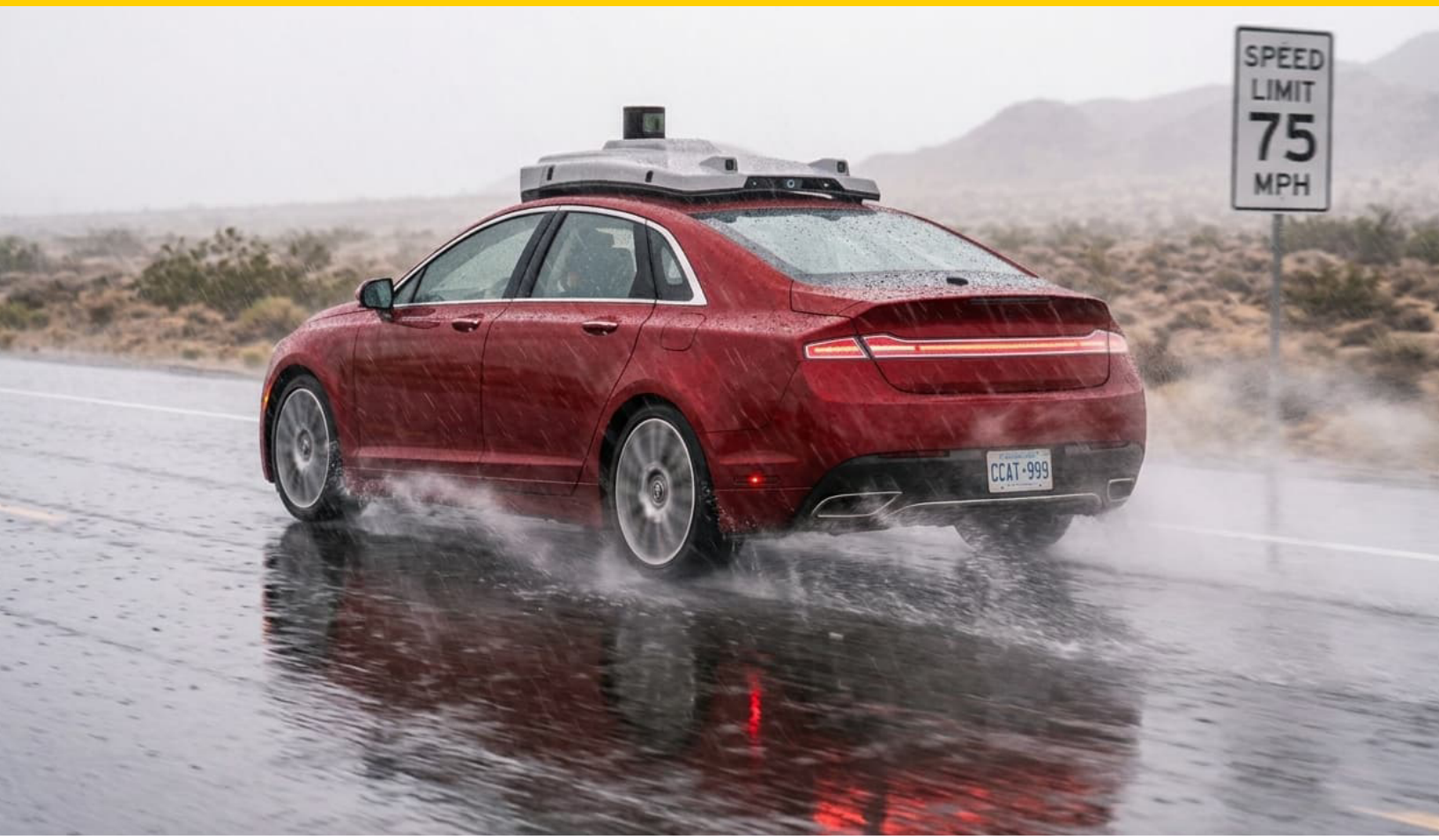
CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Final Report #85
September 2026



Insights on High-Speed AV Operations and Human-Machine Interactions

Kendrew S. Agbermadzo
Yuvraj A. Sehgal
Jiayu Zhu
Fanta Camara
Samuel Labi

PURDUE UNIVERSITY

CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Report No. 85
Project Start Date: June 2023
Project End Date: September 2026

September 2026

Insights on high-speed AV operations and human-machine interactions

Kendrew S. Agbemadzo
Researcher

Yuvraj A. Sehgal
Researcher

Jiayu Zhu
Researcher

Fanta Camara
Visiting Research Fellow

Samuel Labi
Professor

University of York
Purdue University

ACKNOWLEDGEMENTS AND DISCLAIMER

The Center for Connected and Automated Transportation (CCAT) provided funding for this research, under Grant 69A3552348305 of the University Transportation Centers Program, Office of the Assistant Secretary for Research and Technology (OST-R), U.S. DOT. The authors acknowledge the support of various individuals and organizations that provided valuable institutional, material, or cost-share resources for this project. These include Nine/Twelve (Chad Pittman, Kent Anderson, and Doug Rapp) and Dan DeLaurentis (Purdue University's Executive Vice President for Research). The authors acknowledge the direct and indirect support provided in various forms by the members and founders of Purdue's erstwhile Black-and-Gold Racing team (Joe Pekny, Eric J. Dietz, Aly El Gamal, Mike Saxon, Rohan Manna, Shyam Kannan, Manuel Valencia Mar, Haoguang Yang, Alec Pannunzio, Andres Moreno, Richard Ajagu, Sashank Modali, Zainab Saka, and Jiqian Dong), Eckhard Groll, Arvind Raman, Shreyas Sundaram, Shaoshuai Mou, Dan Williams and Purdue AI Racing students and professors, and the IAC. We also appreciate the support from Danny White (former Purdue Motorsports Director), Andrew Goeden (AKS), and Jack Silberman (of UC San Diego's Triton Racing team). The institutions and individuals that provided valuable in-kind cost share or other material or support are acknowledged. These include the Indiana DOT Research Office (Samy Noureldin & Barry Partridge), National University of Singapore (G.P. Ong), ETH Zurich (Bryan Adey), Al Qasim University (Majed Alinizzi), King Khalid University (Saeed AlQadhi), and TU Delft (Goncalo Correia), The World Bank (Ahmed Zulfiqar) Georgia Tech (Adjo Amekudzi & Srinivas Peeta) and the Build America Center (Deepak Benny and Qingbin Cui).

The contents of this report reflect the views of the authors who are responsible for the facts and accuracy of the information presented. This report is disseminated under USDOT's University Transportation Centers program sponsorship in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Suggested APA Format Citation:
Agbemadzo, K. S., Sehgal, Y. A., Zhu, J., Camara, F., & Labi, S. (2026). *Insights on high-speed AV operations and human-machine interactions* (CCAT Report No. 85). The Center for Connected & Automated Transportation, Purdue University.

Credits: Grammarly, ithenticate, and LLMs served as some of the tools used for enhancing the language and the consistency of the narrative, cover design, and cross-checking some of the information presented in this report.

Disclaimer: One of the authors advised and partly sponsored (through this grant) some of the Purdue racing teams whose experiences appear in various sections of this report.

Contacts

For more information

Samuel Labi, Ph. D.
Purdue University
550 Stadium Mall Dr.
Phone: (765) 494-5926
Email: labi@purdue.edu

CCAT
University of Michigan Transportation Research Institute
2901 Baxter Road, Ann Arbor, MI 48152
umtri-ccat@umich.edu
(734) 763-2498

Technical Report Documentation Page

1. Report No. 85	**2. Government Accession No.**	**3. Recipient's Catalog No.**
4. Title and Subtitle Insights on high-speed AV operations and human-machine interactions		**5. Report Date:** September 2026 **6. Performing Organization Code** N/A
7. Author(s) Kendrew S. Agbemadzo (0009-0006-6158-8970), Yuvraj A. Sehgal (0009-0002-8465-1443), Jiayu Zhu (0009-0006-4271-4556), Fanta Camara (0000-0002-2655-1228), Samuel Labi (0000-0001-9830-2071)		**8. Performing Organization Report No.** N/A
9. Performing Organization Name and Address Center for Connected and Automated Transportation, Purdue University, 550 Stadium Mall Drive, W. Lafayette, IN 47907		**10. Work Unit No.** **11. Contract or Grant No.** Grant No. 69A3552348305
12. Sponsoring Agency Name and Address U.S. Dept of Transportation, Office of the Assistant Secretary for Res. & Tech., 1200 New Jersey Ave. SE, Washington, DC 20590		**13. Type of Report and Period Covered:** Final report, Sep 2026 **14. Sponsoring Agency Code:** OST-R

15. Supplementary Notes
Conducted under the U.S. DOT Office of the Assistant Secretary for Research and Technology's (OST-R) University Transportation Centers (UTC) program.

16. Abstract
As the world transitions towards driverless mobility, stakeholders seek to ensure that at high-speed road sections, key transportation outcomes (safety and travel efficiency) are not unduly impaired by this evolution. High-speed operations place demanding constraints on every aspect of the driving automation stack because the spatial extent that must be perceived and the temporal urgency of response both scale unfavorably with velocity. Through a review of literature and a short documentation of racetrack experiences, the present study sheds light on the challenges associated with the prospective deployment of autonomous vehicles (AVs) at high-speed road corridors. This is done by developing insights inferred from published literature which in some cases include documented evidence of the lessons learned from autonomous racing events. This is done from the perspective of the AV functional modules and human-machine interaction (HMI) aspects. Regarding the AV functional modules, the study identifies several high-speed related challenges in the areas of perception and sensing, localization and mapping, prediction and situation awareness, path planning, vehicle control, and compute resources. Then, regarding the various HMI aspects, the study identifies high speed related challenges in the areas of takeover and handover dynamics, driver state and readiness monitoring, information presentation and cognitive load, trust calibration and explainability, external HMI and road-user communication challenges, and ethical and behavioral predictability. The study also throws light on the interrelationships between AV module-related operational limitations and HMI challenges at high speed, in at least three ways: high speed leaves a very short time budget for sensing, deciding, and action; the technical difficulties associated with the AV functional modules propagate directly into HMI difficulty; HMI sophistication may be competing with the AV modules for limited computing resources. To mitigate the AV module and HMI challenges encountered by AVs at high-speed road sections, the study develops recommendations regarding standards (on road infrastructure standards, sensors, and cyber infrastructure), safety validation, seamless and efficient integration of ADS components, human-centered systems and system-of-systems considerations. These recommendations can help inform AV module and HMI design, AV-cognizant infrastructure design and management, and AV-related policymaking to support AV operations at high-speed public roads.

17. Key Words Autonomous vehicles, High speed, Racing, Human-machine interactions; Human factors	**18. Distribution Statement** No restrictions.		
19. Security Classif. Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 83	**22. Price**

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

TABLE OF CONTENTS

LIST OF TABLES 6

LIST OF FIGURES 6

LIST OF ACRONYMS 7

GLOSSARY OF TERMS 8

CHAPTER 1 INTRODUCTION 10
1.1 Background and Study Motivation 10
1.2 Study Objectives 11
1.3 Methods and Data Sources 12
1.4 Related Work at the USDOT Region V UTC (Center for Connected and Automated Transportation (CCAT)) 13
1.5 Discussion 14
1.6 Organization of this Report 15

CHAPTER 2 AV MODULE OPERATIONAL CHALLENGES AT HIGH-SPEED ROAD SECTIONS 16
2.1 Introduction 16
2.2 High-speed Autonomous Land-vehicle Competitions 17
2.3 Transferability of Insights from autonomous racing to autonomous vehicle operations at high-speed public roads - The Need for Circumspection 20
2.4 Fundamental Limitations of AV Operations at High Speed 21
2.5 AV Module-based Classification of the Challenges 27
2.6 Factors that Aggravate Operational Limitations of AV at High Speed 29
2.7 Resolving the Technical Limitations of AV Operations at High-Speed Roads 32
2.8 Standards, Regulations, and Testing Frameworks 37
2.9 Authors' Field Observations from Autonomous Racing Events 40
2.10 Discussion 41

CHAPTER 3 AV HUMAN-MACHINE INTERACTION CHALLENGES AT HIGH-SPEED ROAD SECTIONS 42
3.1 Introduction 42
3.2 HMI Challenges of AV at High-Speed Road Sections 43
3.3 HMI Aspect based Classification of the Challenges 46
3.4 Current Solutions and Their Limitations 50
3.5 Real-World Evidence and Safety Case Studies related to HMI 51
3.6 Discussion 53

CHAPTER 4 CONCLUDING REMARKS 55
4.1 Summary Concluding Remarks, and Discussions 55
4.2 Recommendations 56
4.3 Caveats on Transferability 59
4.4 Avenues for Future Research 59

CHAPTER 5 SYNOPSIS OF PERFORMANCE INDICATORS 61
5.1 Part I of USDOT Performance Indicators 61
5.2 Part II of USDOT Performance Indicators 61

CHAPTER 6 STUDY OUTCOMES AND OUTPUTS 63
6.1 Outputs 63
6.2 Outcomes 64
6.3 List of Impacts 64

REFERENCES 65

APPENDICES 78
Appendix 1. Publication Abstract 78
Appendix 2. New Courses at Purdue University Motivated by this CCAT Project 79
Appendix 3. Autonomous Racing Competitions where Purdue University Teams were Partially Supported by this CCAT Project 82
Appendix 4. FHWA Vehicle Classes 84

LIST OF TABLES

Table 1: Comparison between autonomous racing and autonomous vehicle operations at high-speed public roads 21
Table 2: Synthesis of the HMI challenges at high speed 27
Table 3: Synthesis of the HMI challenges at high speed 46

LIST OF FIGURES

Figure 1: Data collection and extraction procedure used in this study 12
Figure 2: The Autobahn, Germany. This high-speed road system has no general mandatory speed limit on most open, rural stretches but features an official advisory speed limit of 81 mph 17
Figure 3: Major high-speed land autonomous vehicle competitions 18
Figure 4: Major limitations of AV operations at high speed 22
Figure 5: Minimum distance required for AV to stop at high speeds (adapted from Othman, 2021) 23
Figure 6: Aerodynamic sensors help reduce drag; however, large size may compromise such benefits 26
Figure 7: Factors aggravating AV operations at high-speed road sections (human operator factors excluded here 29
Figure 8: Weather and other atmospheric conditions (Viktor and Kiss, 2026) can exacerbate sensor limitations at high speed 30
Figure 9: Proposed solutions for existing limitations of high-speed AV road operations 33
Figure 10: Major HMI challenges in high-speed AV driving 43
Figure 11: Existing HMI solutions in high-speed AV driving 49
Figure 12: AV operations at high-speed roads – Some recommendations 57

LIST OF ACRONYMS

A2RL	Abu Dhabi Racing League
AAA	American Automobile Association
AASHTO	American Association of State Highway and Transportation Officials
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving Systems
AEB	Automatic Emergency Braking
AKS	Autonomous Karting Series
AV	Autonomous / Automated Vehicle
BAHS	Blind at High Speed
CAV	Connected and Automated Vehicle
CCAT	Center for Connected and Automated Transportation
DARPA	Defense Advanced Research Projects Agency
DDT	Dynamic Driving Task
DMS	Driver Monitoring System
FHWA	Federal Highway Administration
FMVSS	Federal Motor Vehicle Safety Standard
HD	High Density
HDV	Human-Driven Vehicle
HMI	Human-Machine Interaction/Interface
IAC	Indy Autonomous Challenge
IMU	Inertial Measurement Unit
IOO	Infrastructure Owner and Operator
ISO	International Standards Organization
LKA	Lane Keeping Assist
MPC	Model Predictive Control
MPLA	Market Penetration and Level of Autonomy
ODD	Operational Design Domain
OEM	Original Equipment Manufacturer (also, the AV industry)
NHTSA	National Highway Traffic Safety Administration
RTI	Request to Intervene (also, takeover request, transition demand)
RSS	Responsibility-Sensitive Safety
SAE	Society of Automotive Engineers
SOTIF	Safety of the Intended Functionality
SSD	Stopping Sight Distance
V2I	Vehicle-to-Infrastructure
V2N	Vehicle-to-Network
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
VMP	Validation-Mileage Problem

GLOSSARY OF TERMS

Adaptation	Real-time adjustment of an AV's sensors, algorithms, and control systems to facilitate navigation in unfamiliar, unpredictable, irregular, or fast changing environments to improve mobility and safety.
Automated Driving System (ADS)	Collection of software and hardware that carry out the dynamic driving task.
Delayed Situational Awareness Reacquisition	The lag or slow recovery time a person experiences when trying to rebuild their mental picture of an environment after an interruption, distraction, or task switch.
Disengagement	In the context of an Advanced Driver Assistance System (ADAS), disengagement refers to the moment when the system deactivates or when the driver turns off the system and/or takes over manual control of the vehicle. In some literature, the term disengagement is used (erroneously, arguably) as a synonym for inattention.
Dynamic Driving Task (DDT)	Set of real-time functions (tactical and operational) that operate a vehicle continuously.
Federal Motor Vehicle Safety Standard 127	A federal safety standard issued by the U.S. National Highway Traffic Safety Administration (NHTSA) that mandates Automatic Emergency Braking (AEB) on all new passenger cars and light trucks (gross weight of 10,000 lbs or less).
Ghosting	A state where the autonomous vehicle loses communication with outside world due to human-made actions (malicious, accidental, or negligent) or natural conditions.
Infrastructure Owner and Operator (IOO)	Organizations that own and/or operate the physical (and in some cases, cyber) highway transportation infrastructure. Includes private and public organizations, including local (city, county, and town), state, and Federal departments, toll road and bridge operators, and transit companies or agencies.
Operational Design Domain (ODD)	Minimum set of conditions under which an AV-related component or autonomous system is designed to function without significant problems. ODD may differ across the different levels of vehicle automation.
Original Equipment Manufacturer (OEM)	Company that manufactures, leases, sells, or maintains AV-supporting components or AVs. OEMs define vehicle ODDs and seek to ensure safe operations of the vehicle within a given ODD, typically regardless of the infrastructure provided by the IOO.
Pose	The orientation and position of the AV during motion.
Production vehicle	Identical, mass-produced automobile manufactured for public sale and legal use on public roads, in contrast to non-production vehicle, e.g., racecars (which operate on racetracks or road courses only). May be human driven or autonomous.

Production AV	Production vehicle that is autonomous and operates on streets, roads, and freeways, in contrast to an autonomous racecar that operates on racetracks and road courses only.
Safety	"Safe" autonomous system is one whose software and hardware are designed and operated in ways that lower unreliability, address highly dynamic environments, and/or have minimum vulnerability to human error in hardware operations and software design.
Software Defined Vehicle (SDV)	Vehicle whose software (and not only its hardware) controls and enhances its features, facilitating continuous updates and new functions remotely through over-the-air (OTA) updates, like a smartphone.
SOTIF (Safety of the Intended Functionality)	Safety framework for autonomous and advanced driver assistance systems (ADAS) that prevents hazards caused by system design limits or predictable human misuse, even when components work with zero hardware or software failures (adopted by the global automotive engineering community and codified as ISO (2022a).
Transition Period	Period between little AV market penetration (MP) and near 100% MP; during which the traffic stream is dominated by mixed traffic (HDV and AV) and a growing share of AV MP.

Sources include: SAE, 2018; SAE, 2021; Gopalakrishna et al. 2021, ISO, 2022a, Labi et al., 2023, NHTSA, 2025.

CHAPTER 1. INTRODUCTION

This chapter first introduces the background and the motivations behind this study. It then defines the research objectives, methods and data sources used in this work. It finally describes the organizational structure of the rest of the report.

1.1 Background and Study Motivation

As one of the primary modes of transportation, roads serve as critical arteries that carry significant volumes of passengers and freight, promoting accessibility and mobility, and ultimately, advancing social and economic development. Accessibility (to human activity centers) is provided mostly by local roads such as urban streets that are characterized by relatively low speeds, interrupted flow, non-motorized traffic including pedestrians, and relatively lower road geometric design standards. Roads that provide accessibility, typically, are low-speed facilities often in urban or urbanized environments. Mobility, on the other hand, is provided mostly by high-speed highway corridors (such as interstates and freeways) that are characterized by relatively high speeds, uninterrupted flow, absent non-motorized traffic, and relatively higher road geometric design standards. These are often located in urban areas as limited access beltways or expressways or in rural areas. Intermediate road classes such as arterials and collectors play a dual role in providing both accessibility and mobility to varying extents depending on their rural or urban locations.

In low-speed urban environments, autonomous vehicle (AV) operations are generally considered safer compared with high-speed sections because reaction-perception time constraints are more relaxed in the case of the former. On the other hand, at high speeds, it is expected that the road is less forgiving of errors related not only to the AV's localization, perception, and controls, but also the AV's human-machine interactions. For example, regarding perception, a high-speed AV needs to perceive the downstream road environment far and wide; secondly, the temporal urgency of response scales unfavorably with velocity. There is low possibility of effective response and recovery when perception is degraded by external environmental contaminants. AV sensors are located outside of the vehicle and therefore face a high risk of operational impairment by these contaminants (fog, smoke, hail, etc.), aerodynamic forces, and structural damage (due to collisions with other vehicles or deer). In contrast, the sensors of an HDV (that is, the eyes and ears of the human driver) are located inside the vehicle and thus not subject to these external threats. Also, at high speed, a sudden loss of localization increases the risk of either collision (in the case of land racing at racetracks or road courses), errant movement, or even loss of the vehicle (in the case of autonomous UAVs, boats, and submarines). High-speed operations place demanding constraints on every aspect of the driving automation stack. From anecdotal evidence, these situations are experienced by racing teams during some AV racing events.

In the real world, there are a few instances of high-speed autonomous land transportation on public roads; robotaxis from Waymo, Tesla and Zoox (Amazon) are becoming more common (CNBC, 2025). Until recently, they were mostly limited to relatively slower, non-highway routes. At the time of reporting, autonomous freight mobility has begun on high-speed road sections. For example, Aurora Innovation has begun regular driverless commercial semi-truck deliveries on 240-mile Interstate 45 corridor between Dallas and Houston, and the 600-mile Interstate 20 corridor from Fort Worth to El Paso (Aurora Innovation, 2025; Dallas Innovates, 2025; Wall Street

Journal, 2026).

Further, autonomous operations may not necessarily represent a safer or more efficient alternative to human driving particularly in the short term. Human drivers exhibit some superiority over automated driving systems, for example, they compensate for their high biological latency through a highly evolved cognitive capacity for contextual anticipation, allowing them to smoothly modulate control inputs over extended time horizons; in contrast, an automated driving system processes discrete computational frames and is subject to rigid, cumulative processing delays (Madigan et al., 2018; He and Donmez, 2022). At high-speed road sections, these ADS limitations could severely compromise the safety and efficiency of an AV traveling at high speed.

SAE J3016 provides a taxonomy for driving automation, clarifying the roles of the human driver and the Automated Driving System (ADS) under different conditions (SAE, 2021). The levels are based on the Dynamic Driving Task (DDT), which includes all real-time functions required to operate a vehicle safely, and the Operational Design Domain (ODD), which defines the specific conditions under which a system can operate safely. Level 0 (No Automation) is where the human driver performs the entire DDT, including steering, braking, and acceleration. Level 1 (Driver Assistance) is where the system can assist with one aspect of driving, either steering or speed control, but not both simultaneously. Level 2 (Partial Driving Automation) is where the system can control both steering and speed simultaneously under certain conditions; the human driver must continuously monitor the driving environment and be ready to intervene. Level 3 (Conditional Automation) is where the ADS performs the entire DDT within its ODD; the human, referred to as the fallback-ready user, must be available to take over when the system requests intervention. Level 4 (High Automation) is where the ADS can perform the entire DDT without human intervention within a defined ODD. Level 5 (Full Automation) is where the ADS can perform the entire DDT under all conditions that a human driver could handle.

1.2 Study Objectives

Considering the study background and motivation discussed in the previous section, the present study was guided by the following research question: what insights can be gained from the literature and field tests that could enhance highly automated vehicle operations at high-speed road corridors, regarding AV operational modules and human-machine interaction (HMI)? Regarding the AV functional modules, the study sought to identify the high-speed related challenges in the areas of perception and sensing, localization and mapping, prediction and situation awareness, path planning, vehicle control, and compute resources. Then, regarding the various HMI aspects, the study sought to identify high speed related challenges in the areas of takeover and handover dynamics, driver state and readiness monitoring, information presentation and cognitive load, trust calibration and explainability, external HMI and road-user communication challenges and ethical and behavioral predictability. Then, based on the hypothesis that the AV module-related operational limitations and HMI challenges at high speed are not independent of each other, the study sought to identify the ways in which such interdependency may manifest. Finally, the study seeks to generate recommendations that could help inform AV module and HMI design, AV-cognizant infrastructure design and management, and AV-related policymaking to support AV operations at high-speed public roads. The present study was commissioned by the USDOT, through its Center for Connected and Automated Transportation (CCAT), a University Transportation Center, to address these research objectives.

1.3 Methods, Data Sources, and Limitations

This report includes the anecdotal experiences of the authors and a narrative, source-based literature review referencing industry reports, technical websites, and research articles rather than a systematic review with a formal protocol. Figure 1 presents the data collection and extraction procedure used in this study. Research articles were identified from key academic databases, including IEEE Xplore, Scopus, SpringerLink, Web of Science, ScienceDirect, and arXiv, from 2013 to 2026. Titles, abstracts, and conclusions of the articles were screened to ensure relevance to high-speed autonomous vehicle operations, to serve as a basis for identifying, subsequently, the operational challenges posed to the AV functional modules and HMI. Sources were gathered through structured searches of academic indices and authoritative web sources, prioritizing peer-reviewed journals (e.g., Journal of ITS: Technology, Planning, and Operations; Journal of Traffic and Transportation Eng. (Eng Edition), KeAI; IEEE Transactions on Transportation Electrification; IEEE Transactions on Intelligent Vehicles; IEEE Transactions on Intelligent Transportation Systems; Transportation Research Part C: Emerging Technologies, Computer-Aided Civil and Infrastructure Engineering; Journal of Intelligent and Connected Vehicles; International Journal of Transportation Science and Technology; Proceedings of National Academy of Sciences; Nature Communications; and Sensors). Other sources are standards bodies (SAE, ISO, UNECE), government agencies (NHTSA, NTSB, FHWA, California DMV), and high-quality preprints (arXiv, SSRN) representing current technical state of the art.

Each study was placed into categories based on the topic using keywords identified in the article or report title. Articles and reports classified under more than one topic were counted in each relevant topic category. For the exclusion and inclusion criteria, conference proceedings and peer-reviewed papers that focused on the AV functional modules and HMI were prioritized. In some cases, information originated from industry or non-peer-reviewed sources. Quantitative findings are reported with their original units and source attribution.

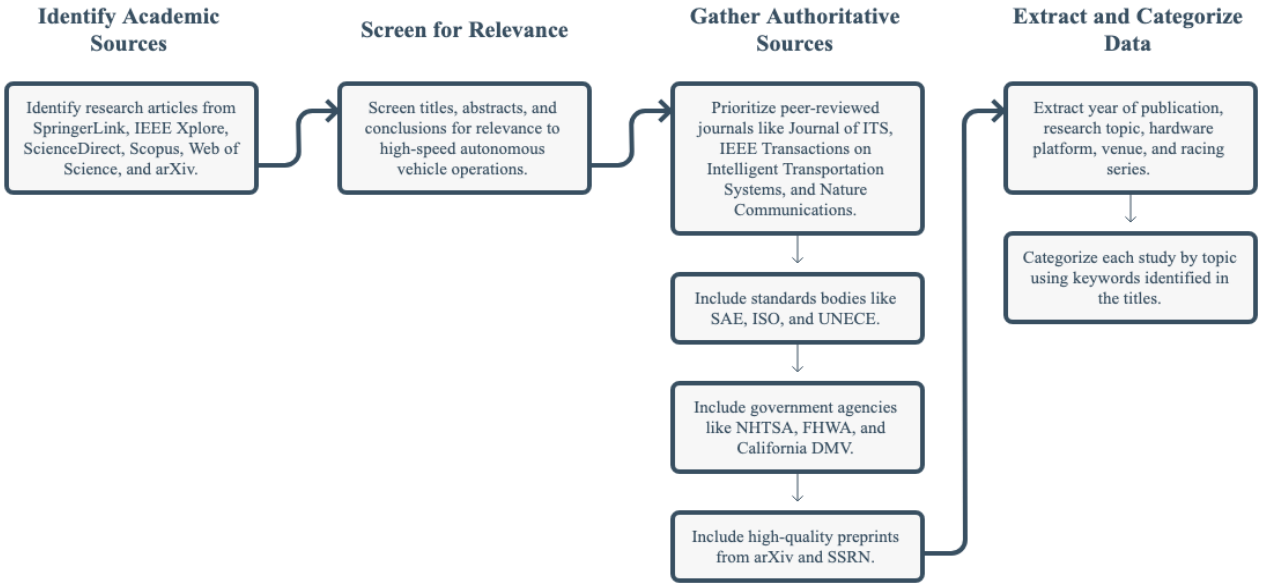


Figure 1. Data collection and extraction procedure used in this study.

The AV racing competitions provided insights into the effect of high-speed operations on the various AV functional modules only and not on HMI. Insights into the HMI aspects of high-speed AV operations were gained only through a review of the literature; none were through the various AV racing competitions described in Section 2.2 and Appendix 3.

The evidence on AV operations at high-speed roads have limitations that are worth mentioning. First, they address on the AV operational modules and not HMI. Second, some of the best recent highway-specific evidence comes from preprints, trucking datasets, or racing-oriented studies rather than from large public datasets of everyday driverless freeway operation. Those sources are valuable because they expose long-range and low-latency constraints more directly, it could be argued that they are not yet a substitute for broad, peer-reviewed evidence from real commercial highway deployment. Third, a significant percentage of literature still relies on simulators, controlled test facilities, or scenario libraries when studying merging, lane-marking degradation, or takeover. That is methodologically appropriate for safety-critical research, but it means the field is only beginning to acquire adequate open, real-world, high-speed evidence on how autonomous systems behave under rare combinations of degraded infrastructure, aggressive human behavior, adverse weather, and communication impairment at scale. This gap is precisely why standards are moving toward scenario-based evaluation and why infrastructure operators and regulators had remained cautious about expanding the ODD for high-speed deployment (ISO, 2022a; ISO, 2022b; ISO, 2025; UL, 2023; UNECE, 2021). Finally, it must be mentioned that the insights presented in this report that are based on author experiences or involvement, company-authored safety data, or anecdotal evidence are to be considered as limitations of the overall narrative.

1.4 Related Work at the USDOT Region V UTC (Center for Connected and Automated Transportation (CCAT))

Perception, path planning, control algorithms, infrastructure preparations and other topics directly related with production AVs at high-speed public road sections have long been the subject of recent Center for Connected and Automated Transportation (CCAT)-sponsored research studies. For example, regarding the use of AI to support high-speed AV operations, Du et al. (2022) created an AI-based fog-cloud control framework with potential application to support high-speed operations of AVs; Dong et al. (2022) created AI-based systems to support safe and effective operations on freeways; and Dong et al. (2023) used explainable AI to improve the perception capabilities of production AVs. Regarding perception and sensing on public roads, Saka and Labi (2023) examined several alternative configurations for sensor placement on an AV; Feng and Tarko (2023) created an AV cooperative perception system; and Feng and Liu (2019) and Feng et al. (2023) designed and implemented AV testing scenario using naturalistic driving data and augmented reality. When an AV is hacked while it is traveling at high speed, the outcome can be detrimental to the safety of the entire traffic stream. Zhang et al. (2026) developed frameworks to harden the CAV ecosystem to reduce cybersecurity risks. The cooperative control technique of Peeta et al. (2022) enables AV platooning which can be useful on high-speed roads.

Regarding infrastructure associated high-speed AV operations, the effects of autonomous truck platooning on freeways were examined by Ramakrishnan et al. (2021); road lane allocation to regular vehicles vs. production AVs was examined by Seilabi et al. (2022); Labi et al. (2023)

discussed the introduction of new classes of assets in the AV era and obsolescence of certain asset types, changes in dimensions of certain highway design elements, and other infrastructure management impacts. Manion and Durango-Cohen (2025)'s framework maximizes investments in transportation infrastructure to support AVs.

Regarding HMI or human factors in general, Guo et al. (2022) developed a VR framework to measure physiological and psychological responses of AV passengers. Anne et al. (2022) used driving simulator environment to determine interactions between infrastructure design and AV user behavior. Molnar et al. (2023) established recommendations to promote inclusive design and deployment of automated vehicles for older adults. Deng et al. (2024) predicted the quality of driver takeover in Level 3 AV (conditional automation).

Liu and Feng (2020) and Liu and Feng (2023) created an AV testing evaluation method and a scenario generation platform, respectively. Gan and Labi (2026) identified and discussed several areas of high-speed driverless racing where production AV stakeholders could learn lessons from autonomous racing events for the benefit of future autonomous mobility. That CCAT study was based on the findings of autonomous racing researchers who are active in autonomous racing competitions worldwide, including Betz et al. (2022), Demeter et al. (2024), J. Betz et al. (2023), and Wischnewski et al. (2022). Others include T. Betz et al. (2023), and Mar et al. (2025).

The present study was not only motivated but also facilitated in part by the active involvement or participation of one of its authors in several high-speed autonomous events at Purdue University and other locations in the United States. It is important to add the following disclaimer: These events, some of which were funded partially using CCAT funds, include the Autonomous Karting Series (AKS) where the current report's co-author is team advisor of the participating student organizations and partial sponsor of two of these organizations (Autonomous Motorsports Purdue and IEEE Autonomous); Roboracer competitions (where the current report's co-author is team co-PI of Purdue's Boiler Autonomy team); and Roboat (Purdue University's autonomous boat sponsored by the US Navy) and IAC's Black and Gold team (later, Purdue AI Racing) where the current report's co-author was a PI and team director. See Appendix 3. Some of the teams' experiences serve as evidence in Chapter 2 of this report.

Also, there were a few CCAT-inspired and in some cases, partially-funded formal academic courses at Purdue University arising from this project. A co-author of this report introduced a few new undergraduate courses for inclusion into Purdue University College of Engineering's Vertically Integrated Projects (VIP) program, as part of this project's educational objectives (see Appendix 2) and an AV-related graduate course at Purdue University. These courses provide formal academic complement to the hands-on autonomous vehicle operations projects and provide a forum for identifying and discussing some of the issues associated with high-speed operations of autonomous vehicles. Additionally, Purdue's annual Autonomy Week and the student-run Next-generation Transport Systems (NGTS) conference offer opportunities for networking and information exchange among graduate and undergraduate students (the future workforce in this area of research and practice), professors, and industry practitioners.

1.5 Discussion

This report presents insights on AV operations and human-machine interactions at high-speed roads and could help achieve the key transportation outcomes of not only safety but also mobility. On urban freeways, expressways and other high-speed roads, this is particularly a relevant

consideration because of growing congestion that will be exacerbated by the complexities of a mixed stream (HDV and AV). To address this problem, AVs operations present a significant opportunity: with their automation and connectivity features, AVs can reduce vehicle headways at high-speed roads, thereby potentially increasing road capacity, and enhancing throughput. This report focus on AV modules and HMI aspects only. However, the impacts of enhanced operations and HMI interactions are expected to resound throughout high-speed road management, including public and private roads, free or tolled. Liu et al. (2022) demonstrated how AVs could be leveraged to enhance the capacity of high-speed roads. S. He et al. (2022) evaluated freeway traffic efficiency impacts of a dedicated lane for connected AVs. Zhang et al. (2025) developed a tolled expressway dedicated lane sharing strategy in a mixed traffic. Chang and Chen (2025) measured the impacts of autonomous vehicles on freeway with conditional isolated and dedicated lanes. Kroes (2026) discussed how self-driving vehicles could reshape toll road demand and revenue. Seilabi et al. (2026) designed a tolling scheme for dedicated AV lanes that is applicable to high-speed urban corridors. These studies provided paradigms that impact demand, ease of operations that could help mitigate AV-module and HMI challenges related to AV operations on freeways and other high-speed roads.

Improvements to the AV modules and HMI interactions are expected to help high speed roads to not only play their key role of mobility but also in a manner that enhances safety and the environment. According to Huang et al. (2024), this is expected to provide opportunities to mitigate traffic congestion, reduce collisions, save energy, and enhance throughput at these roads, as demonstrated empirically by Butila et al. (2026) and Ahnan and Yun (2026). These benefits are applicable to both personal (individual) AVs and AV fleets operating in specific road corridors or networks. Appolloni and Caramia (2026) presented an optimization framework for automated and human-operated fleet routing and Ha et al. (2025) discussed autonomous vehicle fleet operations on road networks that typically include urban freeways and expressways. As more companies operate automated logistics fleets (CNBC, 2025; TruckNews, 2026), the urban logistics operations ideas presented in these studies will reverberate further in all urban road contexts, including high-speed roads that encircle or bypass cities (beltways) and other limited-access thruways that cut through cities.

1.6 Organization of this Report

Chapter 1 introduces the report. This includes the study background and motivation, study objectives , methods and data sources, related work at the Center for Connected and Automated Transportation (CCAT), and a discussion of some wider issues related to limited access road (which typically feature high speed operations) in an era of autonomous operations. Chapter 2 identifies the fundamental AV operational limitations at high-speed public roads, the exacerbators of these limitations, and potential ways to mitigate some of these exacerbators. The chapter also discusses the standards, regulations, and testing frameworks associated with AV operations at high speed. Chapter 3 addresses human-machine interaction challenges facing AVs at high-speed road sections and includes discussions on HMI challenges of AV high-speed road sections, current solutions and their limitations, real-world evidence of HMI challenges and safety case studies. Chapter 4 presents the study summary, conclusions, discussion and recommendations, study limitations and avenues for future work. Chapter 5 presents the USDOT performance indicators. Chapter 6 presents the study outcomes, outputs, and impacts.

CHAPTER 2. AV MODULE OPERATIONAL CHALLENGES AT HIGH-SPEED ROAD SECTIONS

This chapter starts with an introduction and provides an overview of major high-speed AV competitions to date. It then delves into the operational module-related challenges that are faced by autonomous vehicles at high-speed road sections by identifying the fundamental operational limitations related to each AV module and discussing potential influencers of these limitations. The modules include localization, sensing and perception, path planning, control, and fusion. The chapter then presents a few standards, regulations, and testing frameworks associated with AV operations at high speeds. Finally, it provides a general discussion on the resolution of the operational limitations of high-speed autonomy on public roads.

2.1 Introduction

High-speed roads are typically (with a few exceptions), multi-lane, unidirectional traffic flow, controlled-access roads built exclusively for motor vehicles, typically with speed limits that can range from 65 mph to 100 mph or more (AASHTO, 2018; Lippold and Vetters, 2014). These roads have highly regulated ODDs characterized by absent complex urban features like pedestrians and intersections. Examples include interstate highways and non-interstate freeways and expressways (in the United States), controlled-access motorways (in the United Kingdom), the Bundesautobahn (in Germany, see Figure 2), Autoroutes (in France), Kosoku-doro (in Japan), Gaosu gonglu (in China), Rodovias (in Brazil), and truck roads, national highways, superhighways, or expressways (in India, Nigeria, and most other countries). Besides these high classes of roads, there exist other roads of relatively lower functional classes that also have high speed limits.

In the current era as the world transitions progressively towards driverless transportation, circumspection is needed to ensure that at high-speed road systems, the road transportation roles (of safety and travel efficiency) do not become unduly impaired by challenges and limitations associated with AV functional modules or HMI. This could be ensured in at least one of several ways. For example, compared to traditional vehicles, AVs could be designed in ways that promote its operational performance at high speed; specifically, sensors could be installed in ways that do not pose increased energy consumption (Vehicle Integration Team at Waymo, 2023; Iona, 2025; Zhao et al., 2025) or do not cause vibrations that could damage the sensors (Schlager et al., 2022; Lee et al., 2022). Lessons can also be learned from AV racing events (Betz et al., 2022; T. Betz et al., 2023; J. Betz et al., 2023; Demeter et al., 2024; Mar et al., 2025; Wischnewski et al., 2022) as such events throw more light on questions associated with prospective AV deployment on high-speed roads. Rangwala (2026) discussed issues related to the transition of high-speed autonomy from the racetrack to the high-speed highway.

This report is not about autonomous racing. However, automobile race events have continuously functioned as testing grounds for automotive innovation. Sparked by racing teams' desire to win races racecar developments eventually culminated in advancements in production vehicles that operate on public roads (Jiang, 2021; Perrone, 2025). This is important in the current era where human society is on the cusp of autonomous mobility and vehicles are migrating from mostly mechanical systems to fully integrated cyber-physical systems, in other words, "robots on wheels." International competitions, which have evolved from isolated academic endeavors to collegiate competitions, offer unique insights into the challenges that production AVs will

encounter in their high-speed operations. In the sections below, we describe a few of these events.

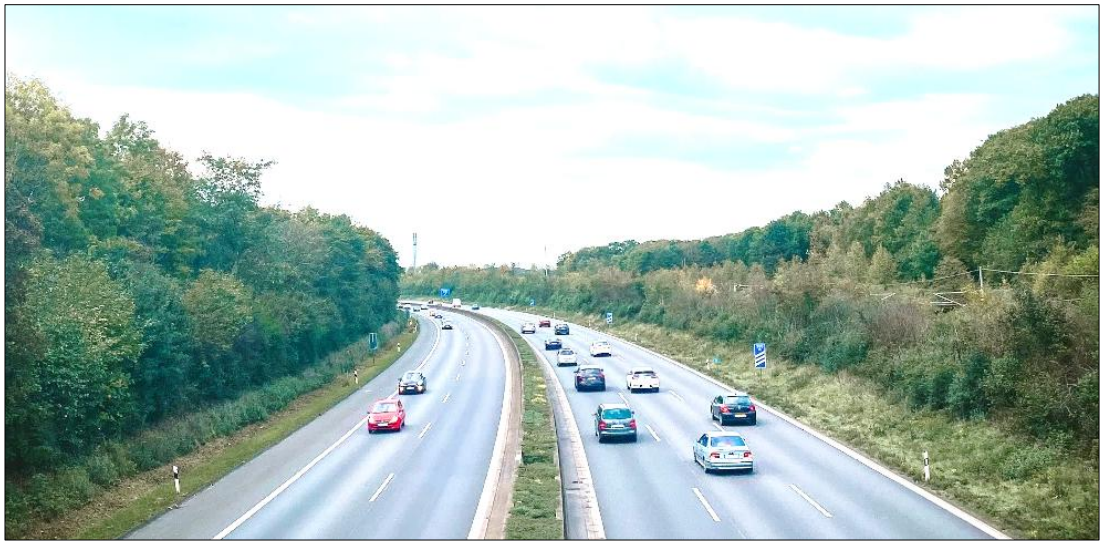


Image source: Jennifer Latuperisa-Andresen, Unsplash
https://unsplash.com/photos/gray-asphalt-road-between-green-trees-under-blue-sky-during-daytime-kM9LrMOCSGA

Figure 2. The Autobahn, Germany. This high-speed road system has no general mandatory speed limit at most open, rural stretches but features an official advisory speed limit of 81 mph.

2.2 High-speed Autonomous Land-vehicle Competitions

Autonomous vehicle racing events involve the assembly of multiple teams at a designated racecourse or racetrack. They feature fully autonomous vehicles of many shapes and sizes such as the 20-inch F-1/10th vehicle (also referred to as "rallycar"), the 6 ft-long AKS go-kart, and larger vehicles like A2RL's Dallara series. On racetracks, road courses, and occasionally guideways with makeshift guardrails or tubing, these vehicles compete at high speeds. To safely navigate the extremes of high speed, the racing teams develop gigabyte-level sensor throughput while maintaining strict millisecond-level latency limits. These competitions offer a living laboratory to stress-test AV perception, path planning, and control modules. The outcomes of these competitions underscore the high-speed AV's critical need for reliable observability of traffic and environmental conditions and instantaneous actuation.

In addition to serving as racing entertainment, these events function as testbeds for verifying different aspects of self-driving technology to promote safety and travel efficiency. Racing AVs have hardware and software systems that bear close resemblance to those of commercially available AVs. As such, the former may offer important lessons for the latter. Gan and Labi (2026) offered examples of how racing evidence could be transferred to public roads with appropriate caveats about the physical and operational differences between a public road and a racetrack. It is worth mentioning that in addition to autonomous racing events, insights could be gained from recently started autonomous trucking operations in Dallas-Houston Corridor and Marysville, Ohio. We describe herein, major AV racing series in the past 20 years (Figure 3).



Figure 3. Major high-speed land autonomous vehicle competitions

2.2.1 The DARPA Grand Challenges (2004-2007)

The US Department of Defense's Advanced Research Projects Agency funds the congressionally approved DARPA Grand Challenges, which are reward contests for autonomous vehicles. The series encourages ground-breaking breakthroughs that convert basic discoveries into useful military and commercial uses (Liu, 2020). Tunnels, tight curves, and difficult desert terrain were all part of the 2005 event. The 2007 Urban Challenge, held at California's George Air Force Base, an urban 60-mile road course with rules on obstacle avoidance, traffic, and roadway navigation, maneuvers, and interactions with other cars (DARPA, 2014).

2.2.2 The Indy Autonomous Challenge (IAC) (2021-present)

IAC, a creation of the Energy Systems Network (ESN), an Indiana-based non-profit offers an avenue for international university teams to compete in a series of challenges to foster excellence in Science, Technology, Engineering, and Math (STEM) at all levels of academia. Supported largely by the Indiana Economic Development Corporation and Lilly Endowment Inc., IAC facilitates not only the deployment of advanced driving systems but also the commercialization of fully autonomous vehicles (IAC, 2025). Simulator competitions and actual racing at test tracks and road courses are frequent components of IAC events. To enable high-speed autonomous racing with an internal combustion drivetrain, the IAC first used the Dallara AV-21, a modified Indy Lights chassis which received major upgrade in 2024 (IAC, 2025). The IAC events, including the recent one in September 2026 at the WeatherTech Raceway at Laguna Seca, CA (Indy Autonomous Challenge, 2026), continue to draw global attention and inspire interest in autonomous racing and autonomous systems in general.

2.2.3 The Formula Student Driverless (2017-present)

This European competition features student-built vehicles that compete in a constrained setting. The program prepares the next generation of workers in autonomous systems so they may gain the knowledge and expertise that OEMs and the autonomous mobility sector are looking for. The competition's financial restrictions push student engineering teams to create creative, affordable solutions in lightweight computing and sensor fusion, which are pertinent to the real world's cost-cognizant mass manufacture of automobiles. Vehicle design, performance, sales presentation, expenses, and business plan are taken into consideration when choosing the overall winner (Long et al., 2024; Global Formula Racing, 2026). This series provides its participants with a lead start in their transition from academic studies and future workplaces (KTH Formula Student, 2025).

2.2.4 The Abu Dhabi Autonomous Racing League (A2RL) (2024-present)

The Advanced Technology Research Council of the United Arab Emirates hosts this championship at the Yas Marina circuit in Abu Dhabi. Teams develop AI software to race standardized, autonomous racecars at high speeds. The EAV-24 chassis used in A2RL's race is based on the SF-23 chassis used in Japanese Super Formula (Autosport, 2025). According to the A2RL websites (A2RL, 2026), the competition helps to push the limits of robotics, artificial intelligence, and autonomous systems with the eventual goal of being used for purposes outside of motorsport, such logistics and passenger transportation.

2.2.5 The Autonomous Karting Series/Purdue University (AKS/Purdue) (2018-present)

Purdue University's electric vehicle autonomous grand prix spawned this international collegiate competition where competing teams undertake design and construction of their autonomous go-karts (AKS, 2026; Purdue University, 2026). The series takes place at Purdue University's Grand Prix Racetrack in West Lafayette, IN and is hosted by a co-author of this report. The series emphasizes minimal use of standardized components and encourages teams to create original solutions. The competition involves the construction and operation of the go-karts, and teams typically consist of students from a wide swath of disciplines: electrical and computer engineering, mechanical engineering, robotics, technology, and civil engineering.

2.2.6 Roborace

In 2015, Denis Sverdlov founded Roborace, probably the world's first global competition for autonomous racing cars. The intention was to test AI and autonomous driving technology and ultimately, to create immersive entertainment through a competition platform and ultimately, to advance road safety. Each competing team used identical chassis and electric powertrains such as the Robocar or DevBot. The hardware was identical across teams; thus, team performance depended solely on software, algorithms, and AI developed by the individual teams (Sytner Group, 2017). Before the series ceased in 2022, they underwent three stages: The Early Exhibitions (in 2016–2018) that demonstrated prototype capabilities during some FIA Formula E Championships; Season Alpha (in 2019) where teams held trial racing events featuring independent teams and early two-car autonomous track contests; and Season Beta (in 2020–2021) where the competing teams navigated unique digital and physical track challenges.

2.2.7 RoboRacer

Created by Rahul Mangharam at the University of Pennsylvania in 2016, the RoboRacer series was motivated by a quest for autonomous systems education and research, including robotics, autonomous racing, communication systems, and reinforcement learning. The event has spread to several universities worldwide, bringing together a global network of researchers, engineers, and fans for autonomous systems. According to RoboRacer (2025), the events aimed to "promote enthusiasm and critical thinking" in autonomous systems. The teams use a standard frame and open-source platform. The F1-Tenth platform is a 20-inch autonomous vehicle that is about a tenth the size of a Formula 1 car (there is no connection with the Formula 1 Motorsport organization).

2.2.8 Other events

In addition to the events mentioned above, there are multiple other similar (albeit smaller scale) autonomous racing events where colleges and high schools worldwide compete at local, regional, national, and international scale (Mohanasundaram and Sai Eshwar Supreet, 2023; Karaman et al.,

2017). A common thread across these events is the provision of standardized (or, in some cases, non-standardized) chassis and AV components (LiDAR, cameras, IMUs, GPS sensors and radars) and onboard computers, and teams generally develop software to ascertain the vehicle's location, sense the surrounding environment, plan the path for movement, and control the vehicle to move along the selected path (Mar et al., 2025). The race cars' hardware is similar (and sometimes, even identical to) that of production AVs on public roads, indicating that the AV industry can learn from autonomous motorsports experiences. Such knowledge could complement insights that could be gained from autonomous trucking tests and operations ongoing at specific parts of the country.

2.3 Transferability of Insights from autonomous racing to autonomous vehicle operations at high-speed public roads – The Need for Circumspection

The racetrack experiences identified in this report – experiential, anecdotal, documented in the cited research literature – provide information that could be helpful towards the design of AV modules, the design of physical and cyber infrastructure to support AV operations, and the development of policy and regulatory standards, thereby helping to promote safe and efficient AV operations on freeways, national highways, and other high-speed road corridors. Many of the insights on the AV modules (regarding latency, vibration, sensing range in particular), learned from racing competitions are transferable to high-speed public roads. However, a few caveats must be presented to highlight the limitations on transferability of some of the insights gained on the racetrack. These limitations, some of which were noted by Gan and Labi (2026) and synthesized in Table 1, arise from the differences between the features between autonomous racing and autonomous vehicle operations on high-speed public roads. Mar et al. (2025) cautioned that not all the autonomous racecar/racetrack challenges translate directly to production AVs on public roads. Regarding guideways, autonomous racing uses a racetrack or road course, whereas high-speed autonomous operations in normal use take place at public roads such as national highways, freeways, or expressways. Regarding vehicle design and dynamics, racecar vehicle dynamics is governed by its low-gravity design and thick tires; some racing competitions use smaller-scale smaller platforms (such as the 1:10-scale in RoboRacer events and 6ft-long platforms in go-kart competitions, whereas vehicles on public roads are consistent with the FHWA Classes 1-14 (see Appendix 4). Regarding guideway access, the autonomous vehicle guideways are closed to non-participants of the race event, and participants are guided by the rules established by the race organizer; in the case of AV operations at high-speed public roads, the guideway is open to all vehicles on public roads, consistent with the FHWA classes (in some countries, high-speed roads prohibit two- or three-wheelers and non-motorized vehicles). Regarding vehicle class distribution (mix of HDV and AV), autonomous racing features AVs only whereas autonomous vehicle operations at high-speed public roads features mixed traffic (HDVs and AVs) except at sections where a dedicated lane or corridor is provided for the AVs. In autonomous racing, cyber infrastructure is set up only during autonomous race event periods, provided by the race organizer or racetrack owner. On the other hand, for autonomous vehicle operations at high-speed public roads, there is permanent cyberinfrastructure, provided by the IOO. Finally, regarding weather, autonomous racing events take place only when the weather is favorable whereas in high-speed public roads, there is no such control and vehicles operate in any weather. In Section 2.8 of the present report, the authors present their field observations at autonomous racing events in the 2023-2026 period.

Table 1. Comparison between autonomous racing and autonomous vehicle operations at high-speed public roads

AV operation feature	Autonomous racing	Autonomous vehicle operations at high-speed public roads
1.Guideway	Racetrack or road course	High-speed road section (national highway, freeway, expressway)
2.Vehicle design and dynamics	Race car design, low-gravity, thick tires. May feature smaller-scale race cars.	Normal roadway vehicles (FHWA Classes 1-14)
3.Guideway access	Open to only the race event participants.	Open to the public; accessible by all vehicles consistent with FHWA classes 1-14
4. Vehicle class distribution (mix of HDV and AV)	Mixed traffic is absent	Mixed traffic is present
5.Cyber infrastructure	Temporary; provided by the race organizer or racetrack owner	Permanent; provided by the IOO
6.Weather	Controlled. Events take place only when the weather is favorable.	Uncontrolled. Vehicles are intended to operate in any weather.

2.4 Fundamental Limitations of AV Operations at High Speed

2.4.1 Prelude

Automated vehicles have demonstrated measurable safety benefits in low-speed urban operations. However, high-speed road sections (freeways, expressways, motorways) present more challenging operational conditions not experienced at low-speed sections. This has been demonstrated amply by autonomous racing teams and researchers that participate in autonomous racing competitions including RoboRacer (O'Kelly et al., 2020; Koirala and Fleming, 2024; Lee et al., 2024; Charles et al., 2025; Qiao et al., 2025), Indy Autonomous Challenge (IAC, 2025; Wischnewski et al., 2022; Reveille Racing and Dietz, 2023; J. Betz et al., 2023), and A2RL (Demeter et al., 2024; Denoyelle et al., 2025; Roles, 2025). Autonomous racing events constitute unique laboratories for investigating AV operations at high speed (Stewart, 2017; Nakamoto and Kobayashi, 2019; Mar et al., 2025; Mirage News, 2025). During competitions, AVs racing teams often experience high-speed operational issues associated with sensing distance, computational burden, latency and computational bottlenecks, sensor vibration and mounting problems, and the aerodynamic adversities, among others, as shown in Figure 4 and further described in the following sections. In the past two years, there has been growing operations of autonomous trucking on high-speed roads (Aurora Innovation, 2025) and these are expected to generate data to provide more data and more insights.

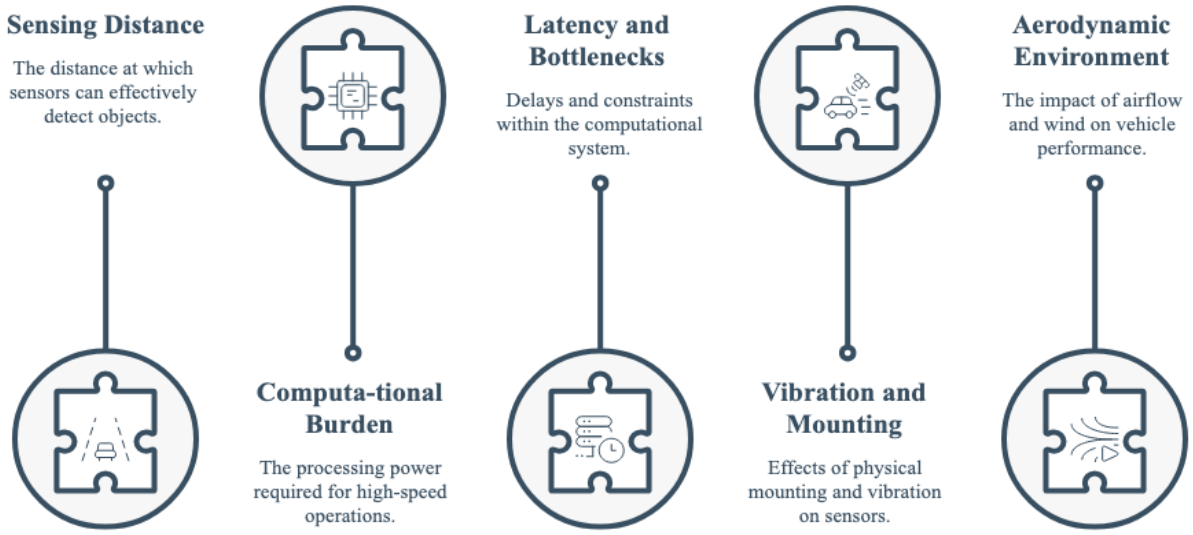


Figure 4. Major limitations of AV operations at high speed.

2.4.2 Perception and Sensing Distance

Sensing distance, a critical element of highway geometric design, traffic engineering, and ultimately, highway safety, refers to the minimum safe distance required for a vehicle to take a preemptive maneuver (reduce speed, stop, avoid, etc.) to avoid a collision (AASHTO, 2018). This distance is a function of the AV speed and the time taken to perceive and react to the roadway threat (Gopalakrishna et al., 2021; AASHTO, 2017; Othman, 2021). Also, sensing distance grows faster than speed, the detection horizon required for safe anticipatory planning exceeds the reliable range of current sensors. The consequences of perception or control failure are more severe. In HDV operations, sensing is done by the human operator through their vision; in AV operations, sensing is done by any one or combination of a suite of sensors including lidar, radar, and camera. Perception challenges include detecting hazards at sufficient distances (a high-speed vehicle needs to identify downstream hazards early enough to respond effectively).

In Othman's study, a reaction time of 0.5 secs was used to generate the minimum time required to safely stop AV and HDV (also, termed the stopping sight distance (SSD), see Figure 5). For example, at 35 mph (56 km/h) and 4% downward grade, the AV (t = 0.5 secs) needs 164 ft. (50 m) to stop; However, at high speed (75 mph (120 km/h)), the same vehicle and at the same grade needs 656 ft. (200 m) to stop. The non-linearity of the scale is evidenced in the charts provided in Othman (2021): higher speeds cause disproportionately higher stopping requirements. In the equation below, the SSD is determined as follows:

$$SSD = 0.278 \times V \times t + \frac{U^2}{254\left[\left(\frac{r}{9.81}\right) \pm G\right]}$$

Where SSD is the stopping sight distance, in m; U is the design speed in km/h; t is the perception and reaction time in s, typically 2.5 secs for HDV and 0.5 secs for AV; r is the deceleration rate in m/s^2, typically 3.4 m/s^2; and G is the road longitudinal grade.

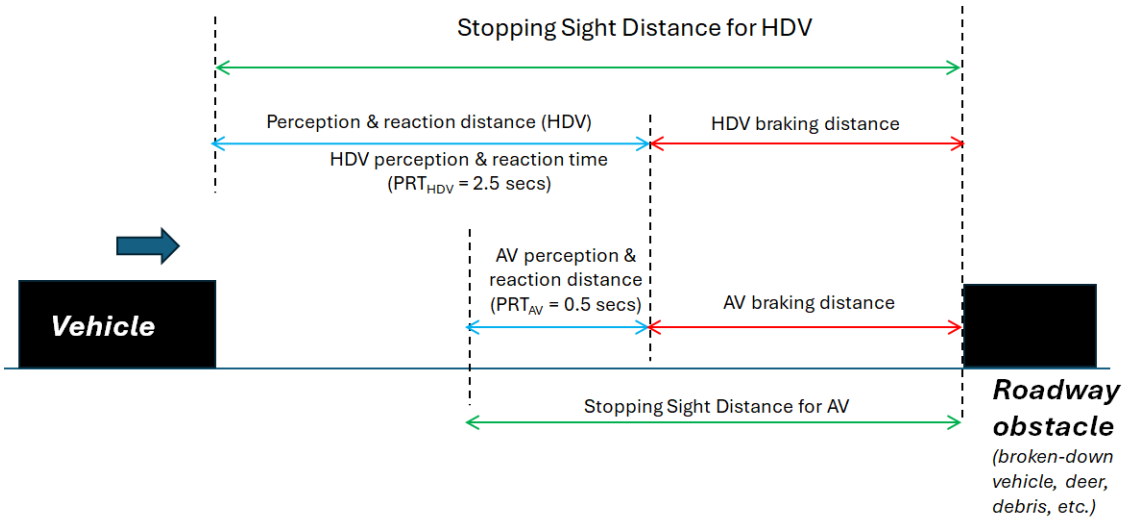


Figure 5. Minimum distance required for AV to stop at high speeds (adapted from Othman, 2021)

It is vital for AV sensing technology to recognize hazards early enough for threat identification, assessment, decision, and action. Detecting an obstacle immediately before reaching it is not useful, even if the detection is technically correct. Therefore, sensing distance represents a formidable operational bottleneck of high-speed AV operations. At high speeds, the distance required by an AV to detect, classify, and safely react to an obstacle can approach or exceed the effective range of cameras/radar/LiDAR, particularly, in adverse weather. Considering the relationship between speed, time, and distance, high speed creates a fundamental problem as it increases the distance over which the environment must be reliably sensed: for example, for a passenger car (t = 2.5 secs) at 68 mph (110 km/h), a minimum distance of 768 ft (232 m) is needed to come to a complete emergency stop.

At high speed, the time available (budget) for perception-decision-action is severely reduced. Highway driving needs adequate lengths of planning horizons and perception ranges. The critical importance of AV sensing capability at high-speed operations is exemplified by Koopman et al. (2019) who used the Responsibility-Sensitive Safety (RSS) model (Shalev-Shwartz et al., 2017) to show that the minimum distance needed for the AV to stop in a worst-case situation (ego AV on ice, lead vehicle on good pavement) may be concerning, considering the range of some sensors in certain environmental conditions. This finding was echoed by Kim et al. (2021). The RSS model (shown below) establishes safe distances ($d_{\min}$) to be maintained by the AV in relation to neighboring vehicles, thereby helping the AV to respond to potentially unsafe situations (Shalev-Shwartz et al., 2017).

$$d_{\min} = \max\left(0, v_{\mathrm{r}}\rho + \frac{1}{2}a_{\max,\mathrm{r}}\rho^2 + \frac{\left(v_{\mathrm{r}} + \rho a_{\max,\mathrm{r}}\right)^2}{2b_{\min,\mathrm{r}}} - \frac{{v_{\mathrm{f}}}^2}{2b_{\max,\mathrm{f}}}\right)$$

ρ is the response time of the driver or autonomous system. v_{r} is the longitudinal speed of the rear (ego) vehicle; v_{f} = longitudinal speed of the front (leading) vehicle; $a_{\max,\mathrm{r}}$ is the maximum acceleration of the rear vehicle during the response time; $b_{\min,\mathrm{r}}$ is the minimum (conservative or comfortable) braking deceleration of the rear vehicle; $b_{\max,\mathrm{f}}$ is the maximum braking deceleration of the front vehicle.

2.4.3 Localization

Accurate localization is critical for the ADS stack (Rehrl and Gröchenig, 2021) because its accuracy and robustness affects the efficacy of not only the other layers of the perception module, but also, the subsequent planning and action modules Chalvatzaras et al. (2022). At high speeds, a small lateral-position error becomes more consequential because the vehicle has less time to correct it. Also at high speeds, the vehicle covers a significant distance during even a brief loss of reliable positioning, and a small error in heading (the direction the vehicle is pointing) can create a substantial position error farther along the predicted path. Localization robustness is particularly important at freeways and other high-speed road sections, narrow work zones and other complex roadway environments where even modest errors may consume much of the available clearance. A few researchers have discussed these challenges. For example, Wischnewski et al. (2019) and Kail et al. (2024) identified localization challenges in autonomous motorsports.

2.4.4 Computational Burden

The AV's operational horizon expands dramatically at higher speeds, leading to sharp increase in the burdens of computation and memory needs, and imposing stress not only on the perception module but also on the entire software stack of the AV. Ghilotti et al. (2026) demonstrated that at high speeds, issues of computational scaling arise, because dense bird's-eye-view and voxel representations scale poorly with range.

2.4.5 Latency and Computational Bottlenecks

A high computational burden has an added effect on the time delay between a user's action and the AV system's response (as the data packet travels from its source to its destination and back). At high speed, this can be a safety-critical issue, because an AV that faces such latency issues while traveling at high speed could be termed "blind at high speed (BAHS)" during which it faces the risk of collision. T. Betz et al. (2023) demonstrated that a lower-latency shared-memory transport reduced perception-to-decision latency significantly, with a corresponding reduction in emergency-braking distance. Latency causes underestimating steering or braking lag; at low speed, this may be merely a passenger comfort or convenience issue. At high speed, this could cause loss of stability during safety-critical maneuvers including emergency lane changes or hard deceleration.

By modeling steering delay as part of a robust MPC design, Kalaria et al. (2022) recognized that delays endanger safety in rapidly changing environments (such as an AV operating in a high-speed section) and found that both computation delay and unavoidable actuation delay must be modeled together. In high-speed vehicle dynamics, not only the digital processing lag but also physical actuation latency constitutes a major mechanical bottleneck. For standard autonomous control designs, steering, throttling, and braking commands are assumed to apply instantaneously; however, the reality is often different (Kalaria et al. 2022).

Mechanical actuators (comprising electric motors, hydraulic pumps, and mechanical linkages) take some time to overcome inertia and execute the digital command, causing an inevitable time lag between the issuance of the control signal and the actual alteration of the vehicle's dynamic state. Consider the actual steering angle (δ_a) treated as a state variable distinct from the desired, computed steering angle command (δ). This mechanical lag is typically approximated using the following first-order ordinary differential equation $\dot{\delta}_a = K_\delta (\delta - \delta_a)$. K_δ is

the inverse of the time constant associated with the specific steering actuator. When this continuous-time dynamic is discretized for implementation within a kinematic bicycle model over a specific time step Δt, the actual steering angle evolves according to the following equation:

$$\delta_{a,k+1} = \delta_k - (\delta_k - \delta_{a,k})(e^{-K_\delta \Delta t} - 1)$$

The total system delay, t_d is calculated as the sum of the internal computation time t_c and the physical actuator command processing time t_a expressed as $t_d = t_c + t_a$. If the vehicle's environmental state is observed at time t, the computed trajectory command does not physically alter the vehicle's trajectory until time $t+t_d$. For example, in a high-speed highway scenario where an AV is traveling at 130 kilometers per hour (approximately 36 meters per second), suddenly faces a hazard, a cumulative system delay of 300 to 400 milliseconds means that the AV will travel 11-14 m in a ghosted state before the avoidance maneuver begins. This underscores the risks posed by high-speed AV operations and the critical need for low latency. Kalaria et al. (2022) presented controller frameworks which showed that accounting for delay compensation at high speed increases the computation time but produces a path prescription that is safer.

2.4.6 Vibration and Mounting Effects on Sensors

The causes of high-speed sensor vibration were identified by Hau et al. (2020), Betz et al. (2022), J. Betz et al. (2023) and Velocity (2023). These include aerodynamic forces (high speeds create turbulent airflow over roof-mounted sensor pods, causing structural flexing); drivetrain and wheel imbalance (unbalanced tires, warped rotors, or driveshaft issues translate high-frequency rotations directly to the chassis and sensor mounts); and road surface excitations (asphaltic concrete bumps, potholes, and faulted slabs) hit suspension components faster, multiplying G-force spikes at sensor locations (Meuer et al., 2024).

Through these mechanisms, AV operations at high speed amplify mechanical resonances, causing high-frequency oscillation of the sensors mounted on a vehicle that degrade LiDAR point-cloud clarity, blurs camera frames, and introduces severe noise into Inertial Measurement Unit outputs or degradation of the outputs of other sensor types (Schlager et al., 2022; T. Betz et al., 2023; Lee et al., 2022); according to these authors, these vibrations impair the AV perception systems in several ways: (a) LiDAR calibration drift: micro-jitters misalign laser emitters and receivers, creating ghost points or distorted depth readings; (b) GPS-assisted INS/IMU saturation: excessive vibration floods inertial sensors with unmodeled noise, making dead-reckoning and orientation tracking unstable. When that happens, the relative pose of camera and LiDAR sensors is altered, significantly degrading perception quality: computer vision becomes blurred as high-frequency shaking strains electronic or software image stabilization and reduces object recognition confidence.

If unaddressed, such sensor drift may cause collisions with other vehicles or pedestrians, or the roadside infrastructure (Lee et al., 2022; Yan et al., 2024). Schlager et al. (2022) carried out vibration testing of an Ouster OS1-64 LiDAR, found a frequency-independent random loss of points and noted that the unit's internal IMU is sufficient for vibration detection only up to 50 Hz above which external IMUs are needed. In high-speed operations, the AV must regularly monitor its miscalibration and duly make corrections where needed.

2.4.7 Aerodynamic Environment

The mounting of sensors on the outer body surface (Figure 6) of an AV facilitates perception and, in some cases, localization. On the downside, however, this causes disruptions to flow surfaces which can be problematic from the perspective of aerodynamics. Large sensors, particularly if non-aerodynamic, create interference effects that alter vehicle aerodynamics and significantly increase drag, increasing energy consumption and noise emissions. Zhao et al. (2025) used steady-state simulations to show that optimized sensor shapes can reduce drag significantly; and found that at low speeds, the aerodynamic effects on externally mounted sensors are minimal; however, at high speeds, incoming headwind disrupts cleaning airflow and any rain droplets on sensor surfaces create attenuation and backscatter that degrade the sensor outputs.

The same broader issue also appears in acoustic sensing, where wind turbulence at cruising conditions can interfere with exterior siren-detection sensors. AVs use acoustic sensors to detect and localize the sirens of approaching emergency vehicles long before they enter the optical field of view. However, at high speeds, aerodynamic flow fields could impair the performance of this sensor type, as high-velocity airflow over the vehicle chassis generates substantial broadband wind noise that can easily mask the specific frequency bands of distant sirens (Sun et al., 2021; Guan et al., 2024). High-speed AV operations require optimal aerodynamic design and placement of sensors, airflow management, and self-cleaning (Zhao et al., 2025).



Image Credit: Leo Visions, unsplash.com/photos/self-driving-car-with-sensors-on-city-street-rT3fpi94lnw

Figure 6. Aerodynamic sensor shapes help reduce drag; however, large sensor size may compromise such benefits

2.5 AV Module-based Classification of the Challenges

In this section, we discuss these challenges categorized explicitly by AV module. Table 2 presents a summary of the operational challenges by AV module. Perception challenges at high speed include sensing range vs. stopping distance mismatch, frame-rate/latency squeeze, motion blur and occlusion, high compute load, and adversarial and edge-case fragility. Localization and mapping challenges at high speed include positioning accuracy pressure, high-density map currentness and reliability, and storage and retrieval latency. Prediction and situation awareness challenges at high speed include trajectory prediction for neighboring vehicles, reduced time for disambiguation, and distribution shift and long-tail exposure. Path planning challenges at high speed include short decision horizons, tightened feasibility options, and semantic-gap corner cases. Vehicle control challenges at high speed include kinematic and geometric controller integrity, validity of the assumption of tire model linearity, MPC computational cost mismatch with real-time deadlines, and actuator delay margin. Compute, power, and thermal challenges at high speed include real-time compute headroom, thermal/power trade-off, and reliability under sustained high load.

Table 2. Synthesis of the operational challenges at high speed, by AV module.

AV Module	Challenges	Details (from literature, race-track experiences, expert assessments, and other sources)
Perception	Sensing range vs. stopping distance	At high speed, the distance required to detect, classify, and safely react to an obstacle can approach or exceed the effective range of the sensors, particularly in adverse weather
	Frame-rate/latency squeeze	Low latency is far less forgiving at high speed compared to low speed.
	Motion blur and small or occluded targets	Fast relative motion increases blur and shortens the window during which a small, distant, or partially occluded roadway object is visible before it must be acted upon.
	Compute load	At any speed, perception already consumes most of the compute budget. Higher speed raises the required frame rate/resolution just as the safety margin for missed frames shrinks.
	Adversarial/edge-case fragility	Perception errors that may be recoverable at low speed may be difficult to recover at high speed.
Localization & Mapping	Positioning accuracy pressure	Lane-keeping accuracy is already demanding at low speed. At high speed, small localization drift translates into proportionally larger heading/lateral error before the next correction cycle.
	HD-map currency and reliance	Compared to low-speed urban driving, high-speed highway driving depends more heavily on prior HD-map reliability. Inaccurate maps are more consequential at high speeds.
	Storage/retrieval latency	Accessing map segments in real time is more difficult when the vehicle traverses map tiles faster (i.e., at high speed).

References that served as input for inferring these challenges include Dong et al. (2026), H. He et al. (2022), Ullrich et al. (2026), Ren and Xia (2023), T. Betz et al. (2023), and Dong et al. (2022).

Table 2. Synthesis of the operational challenges at high speed, by AV module. (Continued)

AV Module	Challenges	Details (from literature, race-track experiences, expert assessments, and other sources)
Prediction & Situation Awareness	Predicting the trajectory of other vehicles	At high speed, the AV's prediction of other road users' future trajectories must reach further ahead in time and space; at high speed, such longer prediction horizon renders future trajectories more uncertain.
	Reduced time for disambiguation	At high speed, AV has less time to resolve ambiguous cues (e.g., the true intent of a merging vehicle) before the AV acts.
	Distribution shift / long-tail exposure	At high speeds, the effect of extreme roadway conditions becomes exacerbated, particularly where such conditions are unrepresented in the AV training data regarding this module.
Path Planning	Shrinking decision horizon	Latency budget is typically tight. Trajectory re-planning in real time is challenging, particularly at high speeds where there is less slack to run computationally expensive optimization online.
	Tightening of feasibility options	At high speed, safe stopping-distance and collision-avoidance constraints emerge as the binding constraints, reducing the feasible trajectory set and increasing the chances of infeasibility of a chosen trajectory.
	Semantic-gap corner cases and black swans	At high speed, sudden adverse roadway conditions (for example, freeway obstruction due to disabled vehicle in a live lane) often fall into the "open long-tail" that rule-based and even end-to-end planners struggle to handle.
Vehicle Control	Integrity of kinematic/geometric controllers	Some rudimentary controllers (e.g., pure pursuit) are known to "overestimate" the needed steering correction and can cause oversteer/skid at high speed because they do not consider vehicle dynamics (tire slip, friction).
	Validity of linear tire models	At high speed, slip/steering angles exceed a few degrees, rendering the traditional linear vehicle-dynamics models inappropriate. For high-speed operations, nonlinear models are generally more appropriate; but these are computationally expensive.
	Look-ahead-distance sensitivity	AV tuning parameters (e.g., look-ahead distance) that work at low speed are highly sensitive and thus could cause path-cutting or instability at high speed.
	MPC computational cost vs. real-time deadline	Model predictive control provides superior safety/comfort trade-offs. However, with nonlinear dynamics (due to high speed), MPC online optimization cost rises sharply.
	Margin for actuator delay	Any latency between planning and actuator response (steering, braking) has greater consequences when the vehicle is moving at high speed, because vehicle state changes faster per unit of delay.

References that served as input for inferring these challenges include Dong et al. (2026), H. He et al. (2022), Ullrich et al. (2026), Ren and Xia (2023), T. Betz et al. (2023), and Dong et al. (2022).

Table 2. Synthesis of the operational challenges at high speed, by AV module. (Continued)

AV Module	Challenges	Details (from literature, race-track experiences, expert assessments, and other sources)
Compute, Power, and Thermal	Real-time compute headroom	Meeting stringent latency requirements across the functional modules (perception, prediction, planning, control) at higher frame rates imposes a burden on onboard compute budget.
	Thermal/power trade-off	Existing automotive thermal/power budgets are tightly constrained even for baseline workloads. Adding compute margin to support high-speed operations (for example, more cameras/higher resolution, faster inference) increases further the heat and power draw.
	Reliability under sustained high load	At high speeds, it is more difficult for fault-diagnosis and health-monitoring systems to detect degraded sensors/actuators fast enough that a fault does not propagate into an unsafe control action before the safety system reacts.

References that served as input for inferring these challenges include Dong et al. (2026), H. He et al. (2022), Ullrich et al. (2026), Ren and Xia (2023), T. Betz et al. (2023), and Dong et al. (2022).

2.6 Factors that Aggravate Operational Limitations of AV at High Speeds

2.6.1 Prelude

As discussed in the previous sections, AV operational limitations at high-speed include impaired sensing distance, computational burden, vibration and mounting effects on sensors, and unfavorable aerodynamic environment. These limitations could be exacerbated further by environmental and infrastructure features, traffic conditions (as summarized in Figure 7 and further detailed in the sections below) and human operator characteristics (addressed in Chapter 3).

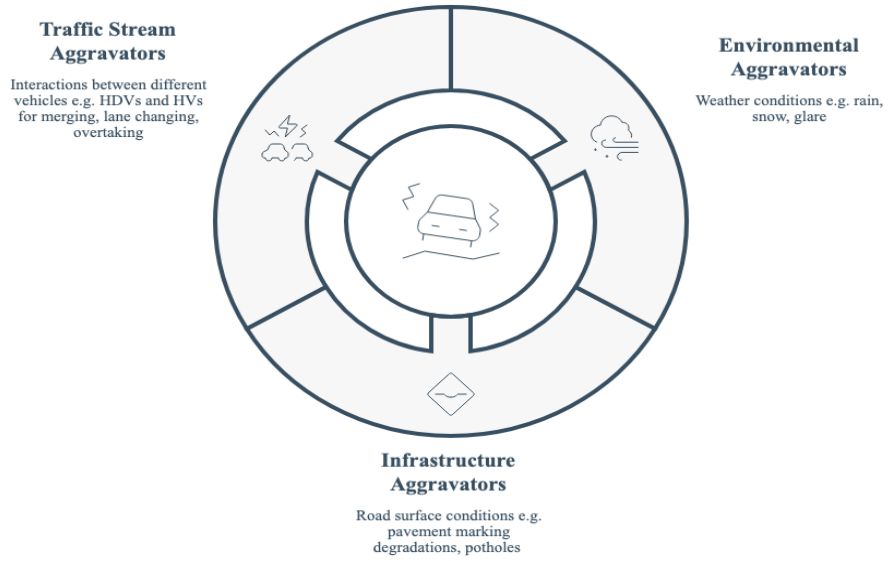


Figure 7. Factors aggravating AV operations at high-speed road sections (human operator factors excluded here).

2.6.2 Environmental aggravators of AV operational limitations at high-speed sections

Adverse environmental conditions generally pose severe constraints to AV operations in general, worsening at higher speeds because the already-small detection horizon shrinks sharply at high speeds. FHWA's Automated Vehicles and Adverse Weather report states that currently available automated systems are not designed to operate in all adverse weather conditions (Neumeister and Pape, 2019). Environmental degradation is often caused by rain, snowfall, fog, glare, and smoke (Vargas et al., 2021; Viktor and Kiss, 2026). For example, glare from direct sunlight or oncoming headlights can temporarily impair visual perception algorithms thereby blinding vision-based autonomous vehicle camera systems, and causing overexposure (Yahiaoui et al., 2020), loss of tracking, and hard braking to avoid collision. Vargas Rivero et al. (2020) suggested weather classification using automotive LIDAR sensors. Gopalakrishna et al. (2021) stated that in bright sunlight, glare could cause insufficient contrast between pavement markings and the pavement, thereby diminishing lane-marking detection. Regarding particulate matter and other objects in the air (that is, fog, mist, rain, and smoke), LiDAR point clouds are impaired in at least one of three ways: spurious noise points from fog/rain/snow particles, reduced range of the LiDAR, and attenuated returns. Camera-based perception is degraded by specular reflections, water spray obscuring lane markings, and reduced contrast in mist and fog.

Viktor and Kiss (2026) identified specific weather conditions that exacerbate sensor limitations (Figure 8). As the figure suggests, camera image clarity can be impaired by precipitation (rain and snow) or airborne solid particles (smoke and dust). In addition, camera and radar sensor performance could be affected by solar glare, and short-wavelength LiDAR and ultrasonic sensors (which rely on air-based signal propagation) can be degraded by haze and fog. Linnhoff et al. (2022) found that there exist vast performance differences across various sensor types in terms of range distribution, atmospheric detections, and attenuation; Viktor and Kiss (2026) found that no single sensor mode provides fully reliable perception in all environmental conditions. Detection models trained predominantly using clear-weather daylight data (Zhang et al., 2023) exhibit pronounced accuracy degradation in rain, fog, snow, and low light conditions. At high speed, lane-keeping and lane changes where stable, low-latency lane interpretation are paramount, such environmental adversities represent an ODD-limiting factor.

RAIN	FOG	SNOW	BRIGHT SUN
Reduced visibility of camera images	Blurred camera images	Lens obstruction	Glare
Signal scattering	Limited range	Snow reflection	Shadows
Radar interference	Attenuated signals	Signal attenuation	Heat distortion
Weak reflections	Poor detection	Iced-over sensors	False returns
	Lidar sensor impairment	Lidar sensor impairment	Overheating

Figure 8. Weather and other atmospheric conditions (adapted from Viktor and Kiss (2026)) can exacerbate sensor limitations at high speed

The effect of sensor surface soiling, particle impingement, and other environmental degradation on AV operational efficacy worsens when the vehicle is moving very fast (Vehicle Integration Team at Waymo, 2023): high-speed motion dramatically increases the kinetic rate at which fouling particles (rain, snow, road spray, fine dust, mud and insects) impinge upon delicate

sensor surfaces. In addition, high speed causes shrinking of an already-marginal detection horizon: researchers have shown that LiDAR cannot reliably detect signs at high precipitation rates and dense fog can significantly reduce effective range (Lee et al., 2023; Khan et al., 2025). Whether the combined effect is sub-additive, super-additive, or neutral is not known. If proven in a future study, sub-additivity of such a relationship would mean that the combined outcome of higher speed and the adverse environment is less than the sum of their individual outcomes; on the other hand, super-additivity would mean that the combined outcome of higher speed and the adverse environment is more than the sum of their individual outcomes. Outcome, in this context, refers to the sensor performance degradation.

A Muddy Situation

At high speeds, large raindrops and dense mud and other high-inertia particles impair sensor efficacy and therefore need aggressive, active mechanical mitigation. Mud represents a uniquely critical contaminant because unlike pure water or ice, it possesses complex and highly variable dielectric properties depending on its specific mineral composition and water content. For radar, the accumulation of mud on the dome causes profound electromagnetic signal attenuation and chaotic scattering, leading to highly unreliable range measurements, false positive obstacle detection, or complete blockage of outgoing and returning radar signals. For LiDAR lasers and camera lenses, mud cover occludes their optical paths, making them entirely blind."

~ Kang et al., 2025; Sabery, 2026.

2.6.3 Infrastructure aggravators of AV operational limitations at high-speed sections

Pavement marking degradation, poor detectability under snow or ice, and dust, and design inconsistency across highway jurisdictions, impair the perception capability of AV sensors, threatening the efficacy of AV operations particularly at high speeds. Also, high speed operations of the AV can be affected by wet nighttime conditions and sun angle. Existing reflectivity standards also pose a problem, as Gopalakrishna et al. (2021) noted that emerging retro-reflectivity standards are still aimed primarily at human visibility rather than machine perception. Wang et al. (2025) evaluated production lane-keeping assist (LKA) systems and found that LKA failures are attributable mostly to faded lane markings, low pavement-lane line contrast, and sharp curvature. Formosa et al. (2024)'s study on lane-marking used data from high-speed roadways, and found that changes in lane-marking appearance caused an increase in traffic conflicts relative to freshly marked baselines, with the worst performance occurring in snowy conditions and very low retro-reflectivity conditions.

Inappropriate infrastructure design may also pose a barrier to high-speed AV operations. Limited sight lines at entrance terminals of high-speed roads contribute to AV merging crashes, and that AV sensor detection range and angle (the sight triangle) may differ from human-driver requirements (Ye et al., 2022). Similarly, large trucks in the traffic stream, buildings, and other infrastructure and roadside features can cause line-of-sight occlusion and restricted geometric field of view of an AV's onboard sensors (Cui et al., 2022). Researchers have emphasized that a favorable roadway environment is critical for AV operations (Hu et al., 2025); a high-speed AV could experience blinding or ghosting which could lead to a collision. Regarding vibration of sensors caused by rough surfaces of road pavements and bridge decks, Schlager et al. (2022) and Hau et al. (2020) discussed how such vibration could damage the quality of camera images.

2.6.4 Traffic stream aggravators of AV operational limitations at high-speed sections

In the foreseeable future, high-speed autonomy will operate in mixed traffic (Favero and Setti, 2024). Such coexistence of AVs and HDVs will persist for an extended period and the dis-uniformity in the traffic stream will engender new safety challenges, particularly in complex maneuvers such as freeway merges and weaving (Cheng et al., 2025; He et al., 2025) at least in the short term (Labi et al., 2023). Freeway merging provides a clear illustration. Chityala et al. (2020) found that drivers at a freeway merge accepted shorter critical gaps as CAV penetration increased. That study found that perceived critical headways for young drivers reduced from 2.9 s at 0% CAV penetration to 1.8 s at 50% and 1.7 s at 75%; older drivers showed the same directional pattern, falling from 3.5 s to 2.0 s and 1.9 s. The same study observed that acceleration and deceleration by merging vehicles affected freeway traffic and occasionally produced collisions. From an operations standpoint, this is important because it suggests that human drivers may adapt their own risk tolerance in response to expected automation behavior, which complicates fixed merging policy for AVs.

Lane changing and overtaking create similar interaction problems. Regarding overtaking, a 2023 study (H. Li et al., 2023) emphasizes that the maneuver is intrinsically complex because it depends on road geometry, relative velocity, oncoming traffic, traffic rules, and environmental conditions, all while requiring a real-time assessment of collision risk and maneuver initiation timing. In highway terms, this means that overtaking is not a generic planning problem; it is a tightly coupled interaction-and-uncertainty problem.

This is why trajectory prediction has become central. A 2025 survey (Xu et al., 2025) describes multi-agent trajectory prediction as critical to autonomous-driving decision systems and identifies five core challenges: complex interactions, dependence on rules and maps, long-term prediction errors, weak generalization to extreme scenes, and real-time constraints. The same review highlights historical trajectories, scene context, and high-precision maps all matter, but that uncertainty in human behavior remains a core unresolved issue. On high-speed roads, the safety effects of these weaknesses are severely amplified at road locations where safety margins are already thin: merging, lane changes, braking waves, and sudden interruptions to the ODD (Xu et al., 2025).

2.7 Resolving the Technical Limitations of AV Operations at High-Speed Roads

2.7.1 Prelude

In this section, the discussion on the resolution of the technical limitations of AV operations at high-speed road sections addresses three of the four classes of exacerbators: environmental, infrastructure related, and traffic stream (the human operator class of exacerbators is addressed in Chapter 3). The palliatives shown in Figure 9 and discussed in the sections below address at least one of these exacerbators. For example, sensor fusion and 4D imaging radar, cooperative perception and V2X, and edge computing, streaming perception, and ML robustness all address the environmental, infrastructure related, and traffic stream exacerbators of AV limitations at high-speed sections.

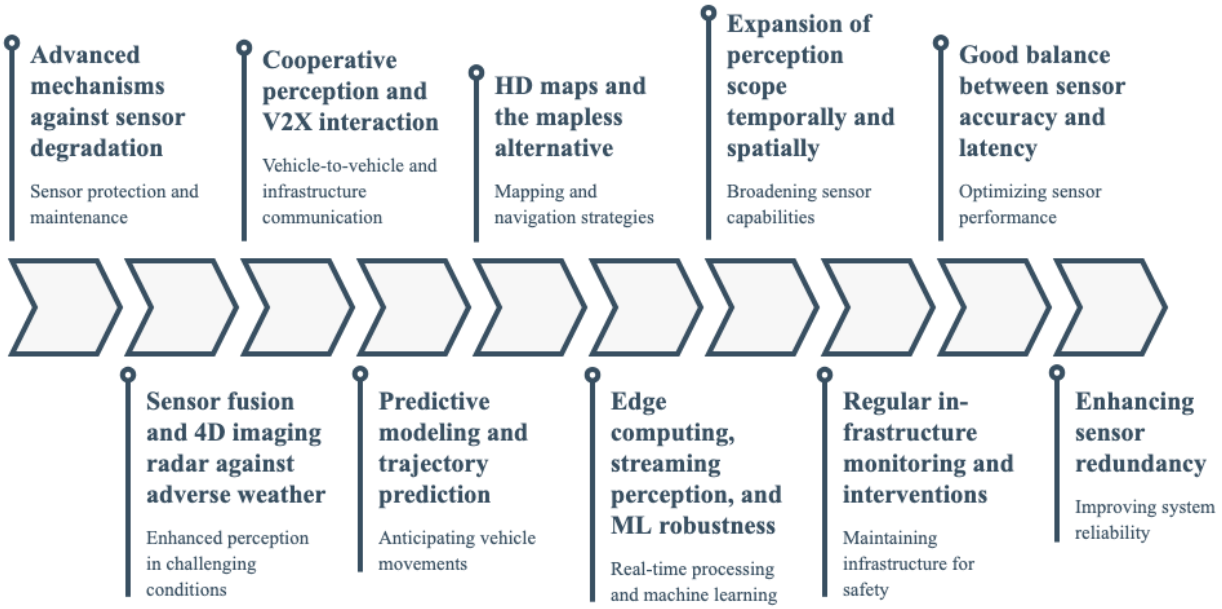


Figure 9. Proposed solutions for existing limitations of high-speed AV road operations.

2.7.2 Addressing sensor degradation caused by environmental soiling and particle impingement

To combat the severe degradation caused by environmental soiling and particle impingement, next-generation sensor cleaning systems have moved beyond traditional windshield wipers (Kral and Dalpez, 2018; Kim et al., 2025). Examples include a synthesized combination of advanced hydrophobic nano-coatings that repel moisture, high-speed rotational lens clearing mechanisms that utilize centrifugal force to shed water, precisely targeted high-pressure air puffers to blast away solid debris, and dynamically optimized washer-fluid nozzles that reduce fluid consumption while ensuring continuous optical clarity. Environmental soiling and particle impingement can profoundly impact sensor performance and the flight paths of small, low-inertia particles (fog droplets, fine particulate matter, etc.) can be altered easily by ambient air pressure. For example, the Vehicle Integration Team at Waymo (2023) suggested that engineering passive aerodynamic deflectors could be installed to re-route incoming airflow over the sensor housings, redirecting these lightweight particles away from the lenses, thereby removing the need for other mechanical intervention.

2.7.3 Facilitating sensor fusion and use of 4D imaging radar

4D imaging radar (adding elevation to range, azimuth, and Doppler velocity) is emerging as a weather-robust complement to LiDAR and cameras, with cost-effective reliability at large distances and direct velocity measurement valuable for high-speed tracking (Yao et al., 2023; Q. Zhao et al., 2026). Frequency modulated continuous wave (FMCW) LiDAR provides simultaneous range and velocity on every point (Bianconi et al., 2025; Wu et al., 2024; Na et al., 2023), which is advantageous for high-speed tracking. However, as noted by these researchers, 4D radar may suffer from multi-path reflections, sparse point clouds, and ghost targets, limiting its stand-alone use. At the current time, this solution is improving rapidly but still primarily a fusion

complement rather than a standalone solution. Due to sensing limitations posed by weather, traffic, vibration, and other factors, probabilistic treatment of sensor uncertainty (Rexer et al., 2025) is espoused by some researchers (Alharbi and Karimi, 2021), and others emphasize regular sensor calibration (Wu et al., 2026) because sensor performance hinges on the technical fit of sensor type, environmental condition, and fusion architecture. Adaptive, uncertainty-aware sensor fusion is a potential solution to perception challenges at high speed. Traditional approaches rely on complex multi-stream architectures which are computationally intensive and may not optimally exploit inter-modal synergies. As such, Yang et al. (2022) presented a single-stream CNN with learnable architecture for multisource remote sensing data, and in a follow-up study, Fasate and Labi (2025) presented a simplified DGConv-Based approach for adaptive sensor fusion. For high-speed roads, the most credible near-term path is therefore not single-sensor minimalism, but reliability-weighted fusion that remains stable as observability changes (Yao et al., 2023).

2.7.4 Cooperative perception and V2X

Cooperative perception, which can help overcome the sensor limitations, relies on robust Vehicle-to-Everything (V2X) telecommunication protocols, enabling connected AVs to continuously share real-time sensor data with neighboring vehicles (V2V), intelligent roadside units and infrastructure (V2I), and overarching cloud networks (V2N) (Yu et al., 2022). Cooperative perception (V2V, V2I, V2X) thus extends the effective perception range and overcomes occlusions by sharing observations among vehicles and infrastructure, directly addressing the single-vehicle range limitation that is most acute at high speed. Datasets such as V2X-Radar demonstrate roadside-plus-vehicle 4D-radar fusion for cooperative perception in rain and at night (Yang et al., 2024). Limitations include communication latency, the need for infrastructure deployment, and amplification of environmental noise during multi-agent communication. This solution has been demonstrated in research and pilots but depends on infrastructure rollout and standardization. V2I and cooperative perception are particularly promising for high-speed roads because they address the line-of-sight and other similar problems directly. USDOT describes connected-vehicle systems as a short-range V2X environment that senses hazards within roughly 300 m and can detect road users that cannot be perceived by line-of-sight sensors. A few cooperative-perception studies show how V2V and V2I data sharing could reduce blind spots, improve range, and lower latency when edge computing is used, while also warning that packet loss, channel congestion, bandwidth, and temporal alignment remain major constraints (US Department of Transportation, 2020; Yang et al., 2024). Cooperative perception architecture appears to be motivated by the inherent physical limitations of single-agent perception (Cui et al., 2022). There is recent evidence that cooperative perception can extend effective perception horizons and support earlier hazard awareness; however, real-world communication constraints remain a key bottleneck (US Department of Transportation, 2020).

2.7.5 Predictive modeling and trajectory prediction

Enhanced predictive modeling and trajectory prediction can help mitigate the limitations of AV module performance at high speed. In this regard, deep-learning trajectory prediction (LSTM encoder-decoder, conditional variational autoencoder (VAE), and related architectures) are leveraged to address interactive merging and lane-change uncertainty, with road-aware methods leveraging HD maps to constrain predictions to feasible paths (Jeong et al., 2020). Xu et al. (2025) identified five challenges: complexity of interactions, rule-and-map dependence, long-horizon

prediction errors, generalization of extreme scenes, and the effect of real-time constraints. Deep models also remain data-hungry, computationally intensive, and limited in interpretability for safety-critical applications. These models are deployed widely but suffer from unresolved robustness and accuracy gaps.

Predictive modeling of expected roadway scenes could be carried out to augment or probably even replace sensor-derived perception scenes. Recent developments are characterized by transformer-based, game-theoretic, reinforcement-learning, and multimodal probabilistic approaches that model neighboring vehicles' possible future paths rather than estimating a single deterministic path. Reduced dependence on static HD maps can be achieved by dynamically updating map layers with V2X inputs and distributed perception; this is motivating a shift from scene prediction based on sensor-acquired knowledge to scene prediction as an extrapolation based on shared and dynamically refreshed information (Lu et al., 2025)

2.7.6 Adoption of innovative mapping technologies – HD maps and mapless images

To support high speed operations, sensors could be supplemented by High-Definition (HD) maps (Gotlib et al., 2026) which support centimeter-level localization and provide priors (lane geometry, traffic rules) to improve planning. However, HD maps are expensive to create and maintain, hard to scale, vulnerable when outdated or inconsistent with dynamic environments, and impose demanding continuous-localization requirements (Casas et al., 2021). This has motivated the increasing adoption of map-less imaging (Ort et al., 2018) and crowdsourced-maps (Dabeer et al., 2017; Herb et al., 2019) such as OpenStreetMap (OSM). Map-less imaging refers to the use of real-time on-board sensors, cameras, and deep neural networks to build temporary "mini-maps" or local views on the fly rather than depending on pre-loaded HD maps. At the current time, HD maps are in use for AV operations, however, their scalability cost could be a challenge, and map-less driving is in a state of growing development.

2.7.7 Edge computing, streaming perception, and ML robustness

To enhance high speed operations, there is a need to mitigate latency. Approaches to do this include forecasting/streaming perception (anticipating where objects will be rather than where they were) and modular latency-compensation networks such as PLM-Net, which mitigates the effect of perception latency without requiring latency itself to be eliminated (Khalil and Bayoumi, 2026; Li et al., 2020). Also, neuromorphic and dynamic-vision-sensor approaches have shown detection-latency promising improvements for high-speed objects in experimental deployments (Mandalapu, 2025) although there is rather limited validation with production AVs. Event cameras also offer a promising low-latency solution by measuring asynchronous changes in intensity to produce motion-rich data which can reduce blind or ghosted times in high-speed scenarios and provide more robustness compared to standard RGB cameras (Gehrig and Scaramuzza, 2024; Madane and Kuan, 2025).

2.7.8 Expansion of perception scope temporally and spatially

Perception challenges at high speed could be mitigated by expanding the temporal and spatial scopes of perception to cover a longer range and time horizon beyond traditional settings. Viktor and Kiss (2026) and Ghilotti et al. (2026) suggest that this could be achieved using a multimodal sensor suite that supports long-range perception, scalability, fail-operational robustness, and end-to-end driving particularly in higher-level automation scenarios. Somewhat related to scope

expansion is the concept of adaptation (Wang and Ghoreishi, 2026), the real-time adjustment of an AV's sensors, algorithms, and control systems to facilitate navigation in unpredictable and irregular environments, to improve safety, and enhance passenger trust. This is particularly critical in high-speed situations where the road scene may be changing at a rapid rate.

2.7.9 Practice of infrastructure management principles

High speed AV operations can be promoted when road ancillary assets (and other roadway supporting (or, unintended debilitating) objects that must be perceived) are made more visible and reliable-for-use. This is done through basic infrastructure management activities: monitor road conditions regularly, establish thresholds for intervention, implement interventions at the optimal times, identify road sections that are most deserving of resources under limited budget conditions, and so on (Labi et al., 2023). The conditions associated with the ancillary assets that can support AV operations at high speed include uniformity, contrast, retro-reflectivity of lane markings and road signs, pavement surface texture and roughness, and clearly marked road medians and guardrails (Ambrosius, 2018; Babic et al., 2022). Addressing these conditions of a high-speed road's ancillary assets can improve not only the road ODD boundary's reliability but also the AV's raw observability (FHWA, 2025), which are critical for high-speed AV operations.

2.7.10 Finding the right balance between sensor accuracy and latency

At any speed, the accuracy and latency of sensing algorithms are important for safety and mobility; at high speeds, this is even more important. Unfortunately, there exists a tradeoff between sensing algorithm accuracy and latency (Li et al., 2020; Aldana-López et al., 2023): faster models reduce delay by sacrificing fine-grained detail while more complex models yield higher precision at the cost of longer computation times. In academic research on AVs, the goal is often to develop accurate but computation-heavy algorithms. Regarding production AVs on the other hand, automotive platforms generally prioritize latency reduction instead (Carnegie Mellon University, 2020). As such, for AV operations on high-speed roads, it can be conjectured that the AV industry may prioritize simpler but faster algorithms that promote faster task execution.

2.7.11 Enhancing sensor redundancy

Sensor redundancy helps but does not fully address the impairment caused by poor environmental conditions. Adding a new sensor does not always scale in terms of overall perception performance. For example, the robustness of radar sensing in poor lighting and weather conditions, and its direct measurement of distance and speed, and its cost and size are superior to camera and lidar, but is limited in terms of angular resolution, sparsity, clutter, and fine-grained object delineation, particularly for small or closely spaced targets (Wu, 2025; Soltanirad and Baghersad, 2025). Yao et al. (2023) caution that additional robustness may not be gained by adding a new sensor type to the sensor suite, and instead advocate enhanced fusion, handling uncertainty, and the selective weighting of sensors based on environmental reliability.

2.7.12 Mitigating sensor vibration induced by poor pavement surface at high AV speeds

In Section 2.6.3, we discussed how addressing poor condition of infrastructure (e.g., deteriorated pavement surfaces) could mitigate impairment of high-speed AV operations. For example, for a high-speed AV traveling on a rough pavement, sensor vibration could cause sensor physical damage or operational impairment. At the vehicle end, this problem could be addressed through

improved vehicle technology (Peng et al., 2026): e.g., dampening of mount movements using tuned elastomeric isolators or rubber bushings to decouple sensor housings from the vehicle frame and stiffening of chassis brackets by shortening or thickening aluminum or carbon-fiber mounting pillars to ensure that resonance frequencies well exceed those corresponding to normal operating speeds.

2.7.13 Sensor housing design

Aerodynamic drag, which occurs at high speeds, affects the AV sensors. Therefore, sensor housing could be designed in a way that minimizes drag, considering a multiplicity of objectives – cost, aerodynamic efficiency, sensor perception efficacy, aesthetics, and so on. Regarding acoustic sensors, there is a need to reduce acoustic interference posed to the sensor due to aerodynamic flow fields. For high-speed operations, housings of AV acoustic sensors should be designed to smoothen the physical airflow around them during high speeds, generating localized aerodynamic "quiet zones" that minimize wind noise susceptibility and preserve acoustic signal integrity (J. Zhao et al., 2026).

Also, environmental soiling and particle impingement at high speeds can have profound effects on the delicate surfaces of a sensor. High-inertia particles tend to bounce off the sensor surface while low inertia particles typically tend to stick to the sensor surface. High-speed motion dramatically increases the kinetic rate at which fouling particles—rain, snow, road spray, fine dust, fog droplets, fine particulate matter, mud, and insects—impinge upon the sensor surface. To protect the sensor surface, the flight paths of these small, low-inertia particles should be altered using passive aerodynamic deflectors. The deflector re-routs the incoming airflow over the sensor housing, diverting the lightweight particles away from the lenses without the need for mechanical intervention (Vehicle Integration Team at Waymo, 2023).

2.7.14 Glare and lighting

To protect sensors from glare conditions at high speed, high dynamic range (HDR) algorithms could be applied to address direct sunlight challenges when AVs equipped with machine vision systems encounter direct sun-facing positions (Paul and Chung, 2018). Also, ODD metrics could be leveraged to enhance AV operations before higher levels of automation can reliably scale in conditions of poor weather (Neumeister and Pape, 2019). Alam et al. (2024) developed approaches for reducing glare across different perception tasks. Esmaeeli et al. (2025) evaluated the efficacy of safety countermeasures against sun glare on AV operations at high-speed road sections. Stone et al. (2020) recommended that AV sensor design could be made to promote AV high speed operations during nighttime or light pollution conditions. These initiatives can significantly promote the deployment of AVs at high-speed road sections under adverse lighting conditions.

2.8 Standards, Regulations, and Testing Frameworks

2.8.1 Prelude

The operational realization of high-speed AV driving is as much a regulatory, legislative, and standardization challenge as it is an engineering endeavor. As such, we devote this section of the present report to this class of non-engineering issues that relate to high-speed AV operations. Standards, regulations, and testing are motivated primarily by safety considerations. In replacing the human driver, vehicle automation is expected to generate a far safer road environment by

preventing a large percentage of crashes at least in the long term. However, the short term (or, the transition period) that is characterized by a mix of HDVs and AVs sharing the same road space), there will likely be a bump in crashes due to immature AV technology, errant human drivers unused to AV operations, and deficiencies related to infrastructure and policy (Papadoulis et al., 2019; Labi et al., 2023). Standards, regulations, and testing will be needed to mitigate this situation in the near-term of AV future.

The questions then are: how much testing is needed to draw confident conclusions about AV safety? Where and how should such testing be conducted? Given the high cost of real-life testing on in-service roads, could testing at operationally limited areas (for example, racetracks or racecourses) and/or testing in a simulation environment help play this role? These questions point to the so-called validation-mileage problem (VMP). VMP, a foundational regulatory barrier, represents the notion that it is not practical to carry out statistical demonstrations of AV safety through on-road mileage. In their RAND study, Kalra and Paddock (2016) reported that the 32,719 U.S. traffic fatalities in 2013 correspond to 1.09 fatalities per 100 million miles, and that to demonstrate AV fatality rate 20% superiority over the HDV rate with 95% confidence is 8.8 billion miles; this would take 400 years with ... a fleet of 100 AVs test-driven at 25 mph, throughout a 24-hr day, 365 days annually. This is not practical. As such, accelerated, virtual, scenario-based, and simulation testing is helpful in this regard. Also, it will be helpful to replicate the Kalra and Paddock study for high-speed road data that is also current.

2.8.2 Functional safety and SOTIF

Two ISO standards are indirectly but strongly related to AV safety at high speeds: ISO 26262 (ISO, 2018) which addresses functional safety (absence of unreasonable risk because of electrical/electronic system failures, was developed to address faults (hazards caused by malfunctioning behavior in automotive electronic and electrical safety-related systems). ISO 21448 (ISO, 2022a) (Safety of the Intended Functionality, SOTIF) addresses hazards that arise without any component failure, from performance limitations, sensor misinterpretation, and unforeseen scenarios. ISO 21448 addresses insufficiency because SOTIF requires reducing the space of unknown-unsafe and known-unsafe scenarios to acceptable residual risk through design, simulation, track testing, and real-world deployments (ISO, 2022a). The difficulty is that the SOTIF objective is broad and it is hard to demonstrate that all edge cases have been accounted for (Bellairs, 2019).

In addressing SOTIF hazards arising from functional inadequacies or foreseeable misuse rather than component failure, ISO 21448's core mandate is to systematically identify and mitigate "unknown, unsafe conditions" prior to public deployment of AVs. Compliance with SOTIF requires highly exhaustive scenario generation and rigorous statistical validation to prove probabilistically that the AV's ODD constraints restrict its exposure strictly to scenarios that the AI is proven to interpret effectively. UL 4600 (Standard for Safety for the Evaluation of Autonomous Products) extends beyond component-level safety by providing a safety-case framework for autonomous products and was described as probably the first comprehensive public-road AV safety standard covering both urban and highway use cases. Together, these documents cover faults, intended-functionality hazards, and evidence-based safety argumentation, but none by itself "certifies" safe high-speed autonomy in the full operational sense (ISO, 2018; ISO, 2022a; UL, 2023). Bellairs (2019) argues that ISO 26262 is fundamentally insufficient for machine learning-driven automated driving systems, where the hardware may function perfectly

according to design. Yet still, a collision may occur if the ADS fails to correctly comprehend a visual edge case, for example, erroneously interpreting the reflection of a truck trailer's shiny side as clear sky.

2.8.3 Regulatory frameworks for high-speed automation

At the current time, high-speed deployment of AVs is bound by relatively narrow combinations of ODD, standards, and national law. United Nations Economic Commission for Europe (UNECE)'s Regulation 157 on Automated Lane Keeping Systems (ALKS) created the first binding international regulation for Level 3 automation for certain highway automation functions (for example, automated lane changes) (UNECE, 2022). The regulation requires that the activated system "shall not cause any collisions that are reasonably foreseeable and preventable." These regulations are significant yet narrow, as they are generally structured for the context of well-defined roads. They are relevant to high-speed road sections that bear these characteristics and are the subject of the present study. TUV SUD (2026) discussed compliance with these regulations.

There are other regulations that apply to road corridors of all speed limits. AV manufacturers must integrate complex Driver Availability Recognition Systems that monitor human readiness to retake control, as well as the continuous recording of a Data Storage System for Automated Driving (an AV black box that records crash event data) (UNECE, 2021). In addition, OEMs must prove simultaneous compliance with UN R155 (Cybersecurity) and UN R156 (Software Updates), linking physical vehicle safety directly to cryptologic digital security (TUV SUD, 2026).

2.8.4 Circumspection in extrapolating existing low-speed guidance to high-speed sections

Testing frameworks are becoming more applicable to specific highway classes, and classes characterized by high-speed operations are of interest in the current study. ISO 34502 (ISO, 2022b) provides a scenario-based safety evaluation framework for ADSs that is applicable to limited-access, high-speed highways, and ISO 34505 (ISO, 2025) adds a methodology for scenario evaluation and test-case generation for Level 3 and higher ADSs. These standards are important because they incentivize migration away from ad hoc demo-driven validation and toward scenario libraries, criticality ranking, and coverage-oriented testing. However, they also reveal the scale of the problem: high-speed safety evidence increasingly depends on massive scenario generation, simulation fidelity, and representative long-tail cases rather than only on road miles (ISO, 2022a; ISO, 2022b).

Until 2024, the strongest published safety evidence of AVs comes from relatively low-speed operations, and such evidence should not be extrapolated to high-speed roads without circumspection. For example, a series of studies by Kusano et al. (2023; 2024) using data from Phoenix, San Francisco, and Los Angeles found significant reductions in any-injury police-reported crashes compared to HDV benchmarks. These operations were generally concentrated in low-speed surface-street ODDs rather than high-speed road corridors. However, recently, Waymo operations and autonomous services have started at road networks that include high-speed road sections (CNBC, 2025), and these are expected to generate data that will be used to further develop AV related safety policy and standards.

High-speed AV operations still lack long-spanned real-life testing data from which guidelines could be developed comprehensively or enhanced. SOTIF requires highly exhaustive scenario generation and rigorous statistical validation. As such, considering ISO 34502, ISO

34505, ISO 21448, and the VMP issue, high-speed AV safety evidence will depend on such massive generation of scenarios, simulation fidelity, and representative long-tail cases rather than only the number of road miles driven (ISO, 2022a; ISO, 2022b; ISO, 2025). A consideration is that high-speed roadways generate fewer interventions compared to low-speed roadways (that are found in dense urban settings). AV incident data such as 2024 California data released by the California Department of Motor Vehicles (2025) constitutes a rich data source for investigating the frequency of disengagements at high-speed road sections (freeways and highways) compared to low-speed sections.

2.8.5 Challenges arising from the multiplicity of jurisdictions

Regulatory hurdles remain particularly visible in the United States. NHTSA's automated-vehicle framework still centers heavily on voluntary guidance, while companies must comply with Federal Motor Vehicle Safety Standards (FMVSS) (U.S. federal regulations that set mandatory minimum performance, design, construction, and durability requirements for motor vehicles and regulated equipment) and certify vehicle compliance themselves. NHTSA's Standing General Order 2021-01 requires manufacturers and operators of ADS and Level 2 ADAS vehicles to report certain crashes involving ADS and Level 2 systems, addressing post-market visibility rather than a unified premarket approval regime (NHTSA, 2021). At the same time, NHTSA's materials emphasize the federal-state split (NHTSA, 2025) and the National Conference of State Legislatures maintains a state-by-state AV legislation database (NCSL, 2026)—evidence of a still-fragmented legal environment. For high-speed ADS, the implication of such legislative fragmentation is that OEMs will face not just technical validation but also multi-jurisdictional operational approval, state law variation, and uneven infrastructure readiness.

2.9 Authors' field observations from autonomous racing events

Autonomous racecars have no human occupant (because they are not designed to have one). As such, the insights from autonomous racing events pertain to the AV functional modules only but not to HMI aspects.

- At high speed, sensors vibrate significantly and, in some cases, become slightly dislocated and give poor outputs. (Purdue University Grand Prix Race Track, Indiana, 2025).
- In certain cases of high speed, the compute resources become overwhelmed due to too much data being transmitted that overwhelm the resources; this has often led to loss of control of the autonomous racecar. (Putnam Road Course, 2023).
- Sensor degradation caused by environmental soiling and particle impingement reduces sensor performance. (Multiple race event locations, 2023-2026).
- Connectivity loss often happens at racetracks, due to occlusion by existing structures and other still-unexplained reasons, that may have led to vehicle disorientation, localization impairment, and in some cases, collisions. (Putnam Road Course, Las Vegas Motor Speedway, 2023).
- Excellent pavement surface condition at high speed is an imperative. At several racing events, racecars have lost control due to a slippery surface, causing problems in vehicle control and other aspects of the autonomy stack. (Multiple race event locations, 2023-2026).

- Some racing teams have added a new sensor to their stack; while this has been helpful generally, it does not always scale in terms of overall perception performance. (Multiple race event locations, 2023-2026).
- Race teams have learned far more from real life track operations compared to simulations. However, simulations are a valuable prerequisite to real life track operations. (Multiple race event locations, 2023-2026).

2.10 Discussion

The central finding of the literature is that autonomous driving on high-speed road sections is a compounded timing problem. Also, this has been the experience of racing teams at high-speed autonomous competition events. A similar finding is expected after data from early ongoing test runs and operations of autonomous trucks along the Dallas-Houston corridor and other routes, are available. At high speeds, longer stopping distances demand earlier perception; earlier perception increases sensing-range and compute requirements; larger sensing horizons increase latency and fusion complexity; and narrow control margins. On high-speed public roads, these challenges are exacerbated by mixed traffic (AVs and HDVs) conditions, adverse weather, and degraded infrastructure. The literature also generally seems to support the notion that even though high-speed roadways are more well defined, they are operationally more challenging compared to low speed roads due to the smallness of the time window for perception and response.

The research also suggests that no single technical breakthrough is likely to remove the challenges faced by the AV functional modules at high speeds. A holistic systems engineering solution seems to be the best way forward: long-range multimodal sensing, low-latency software pipelines, delay-aware control, uncertainty-aware prediction, high-quality lane-marking, well-defined work-zone infrastructure, and V2X or cooperative perception. Current regulations and standards support that direction through constrained ODDs and scenario-based evidence generation.

CHAPTER 3 AV HUMAN-MACHINE INTERACTION CHALLENGES AT HIGH-SPEED ROAD SECTIONS

This chapter starts with an introduction and then describes the main human-machine interaction (HMI) challenges faced by AVs at high-speed road sections. It later provides an overview of existing solutions and their limitations. Finally, it discusses some real-world evidence and safety case studies. Unlike the context of AV module operations, insights from autonomous racing events generally do not apply in the context of HMI, as the racing events use vehicles that do not have a human driver or occupant.

3.1 Introduction

Market Penetration and Level of Autonomy (MPLA) trends (Labi, 2019, Saeed et al., 2021) and market forecasts (McKinsey, 2026) suggest that not only is market penetration of automated vehicles growing but also the average level of autonomy of these vehicles is increasing steadily. ADAS functions that were luxury options are now becoming part of standard packages in vehicles (Russell et al., 2018). The evolution of automation to higher levels will profoundly transform the way drivers interact with their vehicles and will continue to pose safety concern on public roads, particularly at high-speed freeways where the reaction time is minimal and a breakdown in interaction could cause an accident. This report dedicates this chapter to a discussion of the HMI challenges in high-speed autonomous vehicle operations.

In AV operations, safety issues arise where the vehicle can control speed and lane position for extended periods, but a human still must supervise the automated system or take back control when the system reaches its limit. In NHTSA's naturalistic Level 2 study, the ADAS handles lateral and longitudinal control while the driver handles the ADS supervision and takes over the full driving task when warranted. The frequency and intensity of HMI interactions, particularly, the responsibility split between the human driver and the ADS is also influenced by operating speed and the nature of the ODD (Russell et al., 2018).

Regarding high-speed roadway operations, on one hand, high speed reduces the window for reaction and thus induces higher vulnerability to crashes caused by sudden adversities on the roadway. On the other hand, such roads are often characterized by little variation in design features, often causing lower need for take-over vigilance. For example, Reagan et al. (2021) found that use of partial automation on limited-access roads at speeds at relatively high speeds is associated with higher levels of disengagement. The net effect, which may be positive or negative, translates into higher or lower need for enhanced HMI interaction. For a given roadway, the net effect may not be constant over time and might be disrupted by unexpected changes in the roadway environment, such as abrupt hazards on the roadway (for example, incapacitated vehicles on the roadway, work zones, lane-marking degradation, and poor weather).

The "right" takeover of the high-speed AV by the human driver is not always the fastest possible one. In noncritical transitions, drivers often delay control resumption strategically, continuing or wrapping up a non-driving task before re-engaging. Eriksson and Stanton (2017) found that control transition times in noncritical scenarios were substantially longer than the literature had often assumed, and that secondary-task engagement made those transitions slower

and more variable. This is highly relevant to AV driving at freeway and other high-speed roads where planned exits and ODD boundaries are common and where premature assumptions about "standard" takeover time can understate how much margin is really needed.

3.2 HMI Challenges of AV at High-Speed Road Sections

In literature, high-speed AV operations have been identified as a distinct HMI issue. Arguably, as mentioned in the previous section (Reagan et al., 2021), the lack of speed variability (which is characteristic of high-speed corridors) may be yielding some safety benefits (as there is little or no need to take over); this may or may not outweigh the risks posed by the high speed and consequently, little reaction times. However, any disruption to a uniform road environment caused by roadway hazards including work zones, traffic pattern changes, obstacles on the roadway, or the AV exit from the high-speed section to ramp may prompt the need for the human to interact with the AV through, for example, close monitoring or even take over. HMI challenges at high speed include making the driver's role clear, preventing mode confusion, rebuilding situational awareness, allowing enough takeover time, separating response speed from response quality, designing warnings that attract attention, providing useful context without overloading the driver, managing urgency and startle, monitoring driver readiness, and transferring control smoothly, and handling a failed takeover. Figure 10 summarizes the main HMI challenges in high-speed AV driving which are further detailed in the following sections.



Figure 10. Major HMI challenges in high-speed AV driving.

3.2.1 The need for quick perception, multimodal alerts, quicker RTIs, and faster response

In high-speed situations where a Level 3 AV faces a situation it cannot handle, it issues a Request to Intervene (RTI), and the driver must then transition from being a passive passenger to an active driver. The takeover literature consistently shows that takeover efficacy is influenced by the speed of perception, adequacy (effectiveness and redundancy) of takeover alert mechanisms, and

readiness of the human to take over at any time. Several researchers have studied human takeover of ADS at high speeds, mostly in a driving simulation test environment. Zhang et al (2019)'s meta-analysis of 129 studies found shorter mean takeover times when situations were more urgent, when drivers were not using handheld or visual non-driving tasks, when participants had prior takeover experience in the study, and when the RTI included auditory or vibrotactile cues rather than only visual cues or no explicit request. At high speeds, takeover time budgets are low. Short budgets cause acceleration of decision-making and reaction; however, they generally cause degraded quality of takeover which in turn often manifests as higher peak lateral accelerations, harsher braking, and a significantly reduced minimum time-to-collision (Gold et al., 2016). The distinction between "time to touch the wheel" and "quality of vehicle control" is now a central tenet in current-day HMI design for AVs. Arguing that certain forms of distraction could be leveraged as engagement in automated driving, Miller et al. (2015) stated that in-vehicle media use could be managed to allow optimal design of structured takeover transitions.

Some researchers have found that faster is not always safer, particularly where the driver has not yet formed an adequate mental picture of the road scene, selected a maneuver, and stabilized the vehicle. For example, Gold et al. (2013) found that drivers given a shorter takeover exhibited quicker reactions and made decisions faster but made decisions and had reactions that were generally worse in quality (compared to drivers given a longer takeover time). Also, early requests are critical: Pipkorn et al. (2022) found that automated driving need not deteriorate into a highly critical situation if RTIs arrive early enough for preparatory actions to be completed before the real conflict begins. Further, in high-speed environments (where detection and reaction are critical), single mode alerts can be inefficient, as multimodal takeover alerts typically outperform unimodal ones for the initial detection and reaction phases and tactile-inclusive warnings can speed driver reactions across age groups (Huang and Pitts, 2022).

3.2.2 The need for extra situational awareness at high-speed roads.

Situational awareness sits at the center of nearly every high-speed HMI problem. A driver may spend tens of minutes in a low-workload, low-variability environment, then suddenly need to perform a high-quality maneuver. Pipkorn et al. (2024)'s public-road study found that during automated driving, drivers had lower visual attention to the road ahead and made lengthier off-road glances than they do in manual driving. Critically, after an RTI their visual attention did not return to manual-driving levels until more than 15 seconds had passed. That means a driver can be "back in control" in the mechanical sense before being back in control in the perceptual sense. On a high-speed road, that gap is one of the most safety-critical properties of the transition itself.

3.2.3 Driver's complacency or lack of takeover responsibility awareness

On long stretches of a high-speed road, the driver's role may change from being the main driving actor to a supervisory role (Capallera et al., 2023). However, in safety-critical situations during these trips where the driver must take control of the vehicle, the driver must have full situational awareness of the driving environment around the vehicle (Y. Li et al., 2023). Merat et al. (2019) argue that higher levels of driving automation can reduce driver interaction with (and direct control over) the task, thereby compromising the ability to intervene in a timely and appropriate way. Mental workload and situational awareness may tend to decrease as automation increases, while driver reaction time rises (Karimi et al., 2026). This is a characteristic problem at long stretches of freeways and other high-speed road sections. Capallera et al. (2023) reviewed literature on human-

vehicle interaction to support driver's situation awareness in automated vehicles and found that drivers often have a limited understanding of their responsibilities, trust varies with reliability and context, and reduced attention remains a safety problem. For high-speed operations, it is critical for the AV to possess interfaces that keep the human driver in the loop.

3.2.4 Transition from sections of low HMI responsibility to those of high HMI responsibility

A typical trip takes the traveler from their residence through local, low speed streets to moderate speed arterials or high-speed expressways and ultimately to their destination via low-speed local roads. The return trip similarly uses low speed roads to high-speed highways to low speed roads. It can be hypothesized that any time a driver transitions from low speed to high speed or from high speed to low speed, the driver may feel a sense of higher or lower responsibility depending on their level of trust in automation. This could create a mismatch between low-demand supervision during nominal operations and high-stakes intervention during edge cases. The effects of such mismatch could then manifest during human takeover from AV, affecting takeover timing, takeover duration, and takeover quality.

3.2.5 The need for optimal levels of trust

In high-speed operations, the driver should possess the appropriate level of trust in the automated system. Too much trust or too little trust can be detrimental: distrust can cause underuse and hesitation; however, over-trust could lead to shallow monitoring and delayed intervention. Richer state updates and suggested courses of action can help the driver to gauge the extent of their reliance on the automated system (Petersen et al., 2019); therefore, adequate situational awareness support tends to increase trust in automation and improve secondary-task performance. This is an important nuance: For high-speed road operations, an AV needs interfaces that help the driver comprehend quickly, what the automation is doing, what it is not doing, and why a takeover is being requested (Yang et al., 2021).

3.2.6 Need for unambiguous HMI Alerts and appropriate HMI design

The design of HMI in an AV can influence how drivers and road users interact with it (Gong, 2024) and could impact the safety of AV operations at high speed. In a 2023 AAA Foundation for Traffic Safety report, Wang et al. (2023) investigated the effect of two HMI designs in helping drivers return to manual driving after being exposed to four levels of automation (L0-L3) in a straight highway driving scenario with 65 mph speed limit, and found that operators served by a "detailed" HMI (that is, one that provides multimodal warnings with greater specificity) exhibited superior performance, and there were no statistically significant effects of HMI design on lane position, acceleration, other eye glance metrics, for example, on-road glance duration), trust, or usability. A relatively recent study (Hentati et al., 2026) found that "clear and operational human-factors guidelines are essential for autonomous driving" as current HMI guidelines are prone to ambiguity and cannot be easily translated into design or evaluation criteria. They also noted lack of diversity in HMI design in terms of user age and disability status, asserting that users may react differently to alerts provided by the AV. At high speed, this could produce longer reaction times and stopping distances which could increase the risk of collision.

3.3 HMI Aspect based Classification of the Challenges

In this section, we discuss these challenges categorized by each HMI aspect. First, takeover and handover dynamics challenges include compressed handover windows, anticipatory vs. reactive handover, graceful degradation vs. abrupt handoff, and post-handover control smoothness. Second, driver state and readiness monitoring challenges at high speed include vigilance and attention estimation under time pressure, fatigue and complacency at sustained high speed, and mismatch between perceived and actual readiness. Third, information presentation and cognitive load challenges at high speed include interface information load vs. available time, modality selection under time pressure, and alarm fatigue and false-alarm cost. Fourth, trust calibration and explainability challenges include trust calibration under uncertainty, over- and under-trust risks, explainability for real-time decisions, and post-hoc explainability for review. Fifth, external HMI and road-user communication challenges include external signaling legibility at speed, emergency and priority-vehicle interaction, and mismatched expectations with neighboring human drivers in the traffic stream. Finally, ethical and behavioral predictability challenges include the lack of time for in-the-moment negotiation when driving at high speed, consistency across speed regimes, and communication of the trade-off between passenger comfort and safety. Table 3 presents a synthesis of these HMI challenges at high speed, categorized by the six HMI aspects.

Table 3. Synthesis of the HMI challenges at high speed.

HMI Aspect	Challenges	Details (from literature, expert assessments, and other sources)
Takeover & handover dynamics	Compressed handover windows	At Level 3 automation, the time available for an AV driver to reorient, assess the scene, and physically respond after a RTI shrinks in proportion to speed. The gap between "time available" and "time needed" shrinks rapidly with increasing speed.
	Anticipatory vs. reactive handover	Typically, RTIs are issued only after a hazard is detected. At high speed, a request received may already be too late. High speed operations require earlier and more conservative handover triggers. This could increase false-alarm rates and erode driver trust.
	Graceful degradation vs. abrupt handoff	At high speed, abrupt loss of automation is extremely risky because the vehicle's state can diverge quickly from a safe trajectory before the human driver takes over. HMI and control could work together to support minimal risk maneuvers that buy time rather than instantly return full authority to the driver. Without such an integrated framework, the vehicle may veer off course or crash.
	Post-handover control smoothness	Where the human driver takes over a high-speed AV, the abrupt transfer of control could lead to sudden inadvertent responses of the vehicle (for example, sudden steering torque changes) that could startle the human driver or cause overcorrection.

References that served as input for inferring these challenges include H. He et al. (2022), Reagan et al. (2021), Eriksson and Stanton (2017), Zhang et al. (2019), Karimi et al. (2026), Gold et al. (2013), Capallera et al. (2023), Gold et al. (2016), Pipkorn et al. (2022, 2024), Merat et al. (2019), Petersen et al. (2019), Yang et al. (2021), Gong (2024), Wang et al. (2023), and Hentati et al. (2026).

Table 3. Synthesis of the HMI challenges at high speed. (Continued)

HMI Aspect	Challenges	Details (from literature, expert assessments, and other sources)
Driver state & readiness monitoring	Vigilance/ attention estimation under time pressure	At high speed, determination of whether the driver is alert, unimpaired, or physically positioned to resume control must happen fast and reliably. Such determination (via cameras, physiological signals, gaze tracking) could be affected by latency issues because these systems will compete with the same compressed time budget affecting the rest of the stack.
	Fatigue and complacency at sustained high speed	High speed operations typically occur at freeways where there are long stretches of highway automation. This could increase human driver complacency and drowsiness risk. Therefore, at such sections, the driver may be least ready to intervene when needed and will encounter delayed situational awareness reacquisition.
	Mismatch between perceived and actual readiness	In certain cases of takeover, the human driver may believe they are ready to take over when they are not. At high speed, this mismatch is particularly safety-critical because there is less time to discover and correct the error.
Information presentation & cognitive load	Interface information load vs. available time	AVs provide advanced visualizations to convey vehicle state, predicted trajectories, or hazard information that must be perceived, processed, and acted upon. At high speed, the AV has little time to do all this, raising the risk of information overload, tunnel vision, or missed cues.
	Modality selection under time pressure	At high speed, there is less need for interfaces that rely on slow-to-process modalities (dense text, multi-step visual displays); and greater need for faster-to-process modalities (auditory alerts, haptic feedback, glanceable iconography), but these carry their own risks (of being missed or misinterpreted under high speed-related stress).
	Alarm fatigue and false-alarm cost	High speed compresses response time; therefore, systems are often tuned to alert earlier-than-needed or more conservatively. However, frequent or poorly calibrated alerts at high speed can cause drivers to become habituated to warnings. This reduces responsiveness to genuine hazards.

References that served as input for inferring these challenges include H. He et al. (2022), Reagan et al. (2021), Eriksson and Stanton (2017), Zhang et al. (2019), Karimi et al. (2026), Gold et al. (2013), Capallera et al. (2023), Gold et al. (2016), Pipkorn et al. (2022, 2024), Merat et al. (2019), Petersen et al. (2019), Yang et al. (2021), Gong (2024), Wang et al. (2023), and Hentati et al. (2026).

Table 3. Synthesis of the HMI challenges at high speed. (Continued)

HMI Aspect	Challenges	Details (from literature, expert assessments, and other sources)
Trust calibration & explainability	Trust calibration under uncertainty	At high speed, the ability of the HMI to almost instantly convey confidence in an ambiguous situation could be compromised, due to the short time available for deliberation.
	Over-trust and under-trust risks amplified	At high speed, over-trusting the automated driving system could lead to driver complacency, thereby lowering driver readiness. Also, under-trusting could lead to frequent and needless interventions by the driver. Both situations could cause a crash when the vehicle is moving at high speed.
	Explainability for real-time decisions	AI-based and end-to-end architectures are increasingly used in perception-to-planning pipelines. These frameworks yield outputs that are harder to explain in ways that are interpretable by humans. At high speed, there is little time for the driver to evaluate an explanation even if one is provided. Current inability to pre-process explainability into simple, fast-to-parse signals rather than detailed justifications delivered in the moment, can pose a safety-critical limitation at high speeds.
	Post-hoc explainability for review	At high-speed operations, incidents unfold faster, with potentially more severe consequences. Therefore, HMI/logging systems must be able to capture human-interpretable justifications for the system's decisions to support both real-time driver understanding and after-the-fact investigation, regulatory review, and liability determination. At high speeds, such capability is severely constrained.
External HMI & road-user communication	External signaling legibility at speed	External HMI signs intended to communicate the AV's intent to other road users (for example, turning signal for lane changing) must be interpretable immediately from a greater distance to remain useful. At high speed of the AV, the time window for other road users to perceive the signal may be shortened drastically.
	Emergency and priority-vehicle interaction	Time-critical functions such as detecting and reacting to emergency vehicle sirens or signaling to other traffic must take place with adequate lead time to be actionable before the high-speed AV reaches the point in question. Also, any notification by a human occupant to the AV regarding such external safety-critical events must arrive early enough and acted upon promptly to be useful. At high speed, there may be inadequate time for the AV's systems to comprehend and act upon such input.
	Mismatched expectations with human drivers nearby	At higher speed, AVs may experience more ambiguous or unsafe interactions with human-driven vehicles in mixed traffic.

References that served as input for inferring these challenges include H. He et al. (2022), Reagan et al. (2021), Eriksson and Stanton (2017), Zhang et al. (2019), Karimi et al. (2026), Gold et al. (2013), Capallera et al. (2023), Gold et al. (2016), Pipkorn et al. (2022, 2024), Merat et al. (2019), Petersen et al. (2019), Yang et al. (2021), Gong (2024), Wang et al. (2023), and Hentati et al. (2026).

Table 3. Synthesis of the HMI challenges at high speed. (Continued)

HMI Aspect	Challenges	Details (from literature, expert assessments, and other sources)
Ethical and Behavioral Predictability	No time for in-the-moment negotiation	In rare unavoidable-collision-type traffic situations, high speed operations leave extremely short time window for real-time ethical deliberation.
	Consistency across speed regimes	An AV traveling between low- and high-speed road sections will feature reward policies that shift between safety and travel efficiency. This could undermine AV occupant trust and AV movement predictability by other road users. At high speed, therefore, extra effort should be made to communicate the AV's intention to the other road users.
	Passenger comfort vs. safety trade-off communication	At high speed, the AV may resort to aggressive but safety-optimal maneuvers such as hard braking and sharp evasive steering. This can be physically and psychologically jarring for the AV's occupants. Inability of HMI to prepare occupants for such maneuvers could lead to discomfort and even mistrust.

References that served as input for inferring these challenges include H. He et al. (2022), Reagan et al. (2021), Eriksson and Stanton (2017), Zhang et al. (2019), Karimi et al. (2026), Gold et al. (2013), Capallera et al. (2023), Gold et al. (2016), Pipkorn et al. (2022, 2024), Merat et al. (2019), Petersen et al. (2019), Yang et al. (2021), Gong (2024), Wang et al. (2023), and Hentati et al. (2026).

3.4 Current Solutions and Their Limitations

Figure 11 presents the existing HMI solutions in high-speed AV driving. In this section, we discuss HMI personalization for different contexts, time thresholds for alerts, and robust driver monitoring.

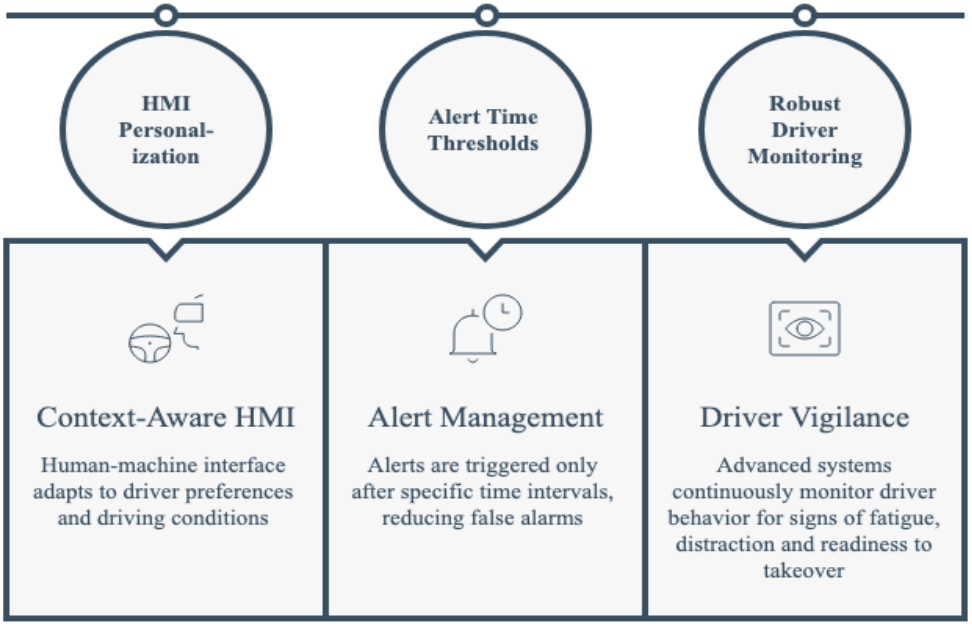


Figure 11. Existing HMI solutions in high-speed AV driving.

3.4.1 HMI Personalization for Different Contexts

Several classes of maneuvers exist on a typical high-speed road section, such as merging, exiting, avoiding a roadway obstacle, etc. The HMI must be designed in a way to handle such variability. In this regard, innovative HMIs include one with user-centered design approach that considers the user's needs and capabilities, the task or scenario context, and a combined bottom-up and top-down approach to align the user's needs with regulatory requirements, such as that proposed by Hentati et al. (2026). There exist two main classes of maneuvers: time-critical and non-time-critical. For example, an AV's exit of the high-speed section to a ramp or crossroad is a non-time-critical maneuver while the AV's braking or changing lanes to avoid collision with a roadway obstacle is a time-critical maneuver. The human takeovers of the automated systems are cognitively different in these two situations. Tan and Zhang (2024) developed a computational cognitive takeover model regarding the AV's exiting a high-speed road section, and found that takeover behavior depends on gaze redirection, task prioritization, situational awareness, and trust, and that a useful takeover interface should provide the reason for the takeover, the remaining distance or time prior to exiting, and information about neighboring vehicles that need attention. The authors also found that models derived from emergency takeover studies are not sufficient for freeway-exit situations because drivers behave differently when they believe they have time. Grobelna et al. (2025) found that simplification and dynamic display of information reduces not only the time taken by the driver to interact with the interface by personalizing the menu layout but also their cognitive load during high-speed driving conditions.

3.4.2 Time Thresholds for Alerts

For planned events that prevent continued automated operation, a RTI should be issued early enough for a minimum-risk maneuver if the driver does not respond, as stipulated in UNECE Regulation 157. The same regulatory framework also requires driver-availability recognition not just recognition based on whether the driver is merely seated behind the wheel. Production AVs have systems that account for this caution; some systems revert control when the threat clears or use a defined fallback-ready-user concept with takeover escalation and an automated controlled stop if the driver fails to respond (United Nations, 2021). There are others that use an adaptive information display approach where only critical alerts are shown to the driver during high-speed or congested road conditions where rapid decision-making is required (Grobelna et al., 2025).

3.4.3 Robust Driver Monitoring

At high-speed road sections, robust driver monitoring is essential. UNECE R157 requires Level 3 systems to determine driver availability to take over the AV based on monitored criteria rather than an assumption of unavailability. In UK, a Transport Research Laboratory (TRL) review (Deans et al., 2025) notes that the UNECE R157 regulation effectively requires positive confirmation of availability, with at least two criteria indicating availability within the last 30 seconds. As soon as the driver is deemed to be unavailable, the system must issue a clear and distinctive warning, followed by an RTI if needed. This is considered a safer alternative compared to hands-on-wheel requirements. The Insurance Institute for Highway Safety (IIHS)'s safeguard rating protocol states that good partial-automation systems should monitor the eyes, head, and hands; and "initiate a bimodal alert within 10 seconds of driver inattention; escalate to a trimodal alert or emergency slowdown within 20 seconds"; and maintain appropriate emergency escalation

if the driver remains unresponsive. IIHS also recommends that automated lane changes be initiated or confirmed by the driver and that lane-centering support remains active during cooperative driver steering, because shared control can help keep the driver mentally and physically engaged (IIHS, 2024a; 2024b). A system could combine multimodal sensor data to monitor driver behavior including detecting signs for fatigue or distraction (Fu et al., 2024) or take a more proactive approach when the driver is unable by taking partial control of the vehicle during emergency situations (Grobelna et al., 2025).

3.5 Real-World Evidence and Safety Case Studies related to HMI

Recent field and naturalistic evidence suggest a more severe driver inattention on higher speed roads compared to lower speed roads. Reagan et al. (2021) found that use of partial automation on limited-access roads at relatively higher speeds is associated with higher levels of inattention and reduced monitoring, with stronger effects appearing after users had more experience with the system. IIHS (2024b)'s work similarly concluded that drivers are more likely to multitask when using partial automation and can learn to work around system attention requirements. Taken together, these studies suggest that automation risk at high-speed roads is dynamic rather than static: behavior may deteriorate after familiarity grows, not just during novice use. In the paragraphs below, we discuss HMI-related safety case studies that have occurred at high-speed road sections in the United States.

3.5.1 The 2018 Mountain View Crash

In this March 23, 2018 crash, the SAE Level 2 vehicle was travelling roughly 71 mph on US Highway 101 in Mountain View, California. The Autopilot was engaged for nearly 19 minutes before the vehicle veered off the highway (NTSB, 2020a). The National Transportation Safety Board also found that the driver was likely distracted by a video game on his smartphone. Investigations also faulted the limitations of the driver-assistance system, deteriorated lane markings, and a damaged crash attenuator that had not been restored. After the crash, recommendations included the need for capability to issue promptly, warnings about any adverse road conditions ahead.

3.5.2 The 2019 Delray Beach Crash

This crash occurred on March 1, 2019, on a high-speed arterial – State Road 7 (US 441) – in Delray Beach, Florida. The speed limit at that section was 55 mph and the SAE Level 2 vehicle was traveling at approximately 68 mph at the time of impact. NTSB noted that the vehicle was operating outside its ODD and reiterated the need for safeguards that limit use to design conditions. This case reflects HMI failure that occurred at high speed of the vehicle: the system permitted prolonged inattention; the driver overestimated what the automation would handle; and the transition back to human control occurred too late or too weakly (NTSB, 2020b).

3.5.3 The 2024 rear-end crashes at San Antonio and Philadelphia

In the San Antonio, Texas crash, an SAE Level 2 vehicle traveling at 74 mph struck a stationary vehicle on Interstate 10 (70 mph speed limit at that location) on February 24, 2024, and in the Philadelphia, Pennsylvania crash, an SAE Level 2 vehicle traveling in a highway workzone section (55 mph speed limit at that location) on March 3, 2024. The NTSB report on these crashes is HIR-

26-02 which was adopted on March 31, 2026 (NTSB, 2026a). The NTSB determined probable causes involving driver distraction and overreliance on the partial automation system, and, in the Philadelphia crash, alcohol impairment; also, the driver monitoring system (DMS) were found to be ineffective in detecting driver inattention or distraction, and not only allowed off-road glances to go unnoticed but also was unable to distinguish between attention to the roadway and attention to objects obstructing the visibility of the road scene ahead (NTSB, 2026b). Coverage of the findings reports that the circumstances were likely outside the capability of the forward collision warning and automatic emergency braking available at the time, and that the findings point to FMVSS 127 (Repairer Driven News, 2026).

3.5.4 Stakeholder-targeted Recommendations by NTSB that Impact Safety of High-speed AV operations

In the wake of the crashes identified above and NTSB investigations, the NTSB (2026b) made several safety recommendations to various stakeholders. Many of these recommendations are directly relevant to high-speed operations. First, the NTSB recommended to the United States Department of Transportation (USDOT) that the USDOT issue guidelines to vehicle manufacturers regarding the deployment of "partial vehicle automation systems that address known system limitations," including (a) integrating and concurrently engaging AEB or other safety-critical technologies (active intelligent speed assistance, driver monitoring); (b) promoting driver engagement through targeted design, (c) lowering safety risks posed by automation misuse or complacency, and (d) establishing "maximum operational speeds for automation systems based on their overall capabilities."

Second, the NTSB recommended to the National Highway Traffic Safety Administration (NHTSA) that the NHTSA should require manufacturers to equip eligible vehicles (that is, new SAE International Level 2-capable passenger vehicles) with telematic capability to notify the manufacturer of any crash that is consistent with NHTSA's reporting requirements. Also, the NHTSA should modify relevant parts of federal regulations to require that all eligible vehicles be able to "record data elements related to these systems, including, at a minimum," (a) system availability, (b) driver alerts, (c) "system engagement and activation denial," and (d) system faults for driver monitoring, AEB, lane centering, forward collision warning, lane departure prevention, and so on. In addition, the NTSB stated that NHTSA should require that eligible vehicles be "equipped with driver monitoring systems (DMS) capable of minimizing driver inattention, automation complacency, and misuse of vehicle automation by, at a minimum, (a) providing warnings about accumulated short glances over a prolonged period of time, (b) differentiating genuine on-road glances from attention directed to objects, such as cell phones, located in the driver's forward line of sight; and (c) issuing initial and subsequent multi-modal alerts at intervals that minimize eyes-off-road duration."

Third, similar to what it recommended to NHTSA, the NTSB recommended to the vehicle manufacturer to revise the DMS in eligible vehicles to provide the capability to (a) detect and disseminate warnings regarding cumulative short distractions (of the driver) over a prolonged time, (b) distinguish between dutiful driver on-road glances vs. errant glances (cell phones, roadside objects, etc. in the driver's "forward line of sight;" (c) and "issue initial and subsequent multi-modal alerts" at frequencies that reduce the propensity and duration of eyes-off-road situations. In addition, the vehicle manufacturer was recommended to modify their ADS for eligible vehicles to require that appropriate engagement of the AEBS; and that appropriate speed tolerances are

established to reduce instances of excessive speeding, considering complexity of the ambient traffic and roadway environment, and the system's operational capabilities.

3.6 Discussion

It can be postulated that the AV module-related operational limitations and HMI challenges at high speed are not independent of each other but are intertwined in a few ways. First, nearly every module-level and HMI-level challenge converges to the same underlying issue: the required look-ahead distance, prediction horizon, information volume, and consequence severity all scale upward sharply at higher speeds; unfortunately, high speed leaves a very short time budget for sensing, deciding, and action. Second, the technical difficulties associated with the functional modules propagate directly into HMI difficulty. For example, perception or prediction uncertainty that is manageable at low speed (where there is more time to disambiguate) suddenly emerges as an HMI problem at high speed, because the autonomous system must either act autonomously under higher uncertainty or hand that uncertainty to a human who has even less time (compared to the autonomous system) to resolve it. Third, compute/latency challenges seem to limit what HMI can even attempt: if the perception-planning-control loop is already consuming most of the real-time compute and latency budget at high speed, then it can be hypothesized that there is proportionally less compute budget left over for driver-monitoring, explainability generation, or rich visualization. This suggests that at high speeds, HMI sophistication is not a bonus feature but rather seems to compete with the functional modules for the same constrained resources.

With growing average level of autonomy and market penetration of AVs in the traffic stream, purely HDV traffic streams are gradually transitioning to a mixed-traffic ecosystem. However, they will likely face the highly asymmetric challenge of navigation in the immediate vicinity of unpredictable, often aggressive, and opportunistic human drivers who, in some cases, may be seeking to exploit the AV's conservative driving style (Li et al., 2026). At high-speed sections, such adversarial interactions could lead to collisions and casualties. At the AV's end, this could be mitigated by greater awareness capabilities of the AV beyond its sensor suite: cooperative perception and V2X communication networks could facilitate sharing of spatial awareness and information on HDV's behavioral hazards well beyond the AV's immediate physical line of sight, and appropriately designed HMI interfaces. This could help neutralize the errant behaviors of aggressive human drivers on high-speed roads.

CHAPTER 4. CONCLUDING REMARKS

4.1 Summary, Concluding Remarks, and Discussions

In the emerging era of autonomous mobility, IOOs, OEMs, road users, and the general public have a stake in the promotion of user safety at high-speed road sections where severe constraints are placed on every aspect of the driving automation stack. High speed makes autonomous driving more difficult for several reasons that are based on a central theme: the spatial extent that must be perceived and the temporal urgency of response both scale unfavorably with velocity. In other words, the vehicle covers more distance during any latency delay; braking distance increases approximately with the square of speed; steering becomes more sensitive; there is less opportunity to recover from mistakes; and the system must look farther ahead. It needs sufficient distance to identify a hazard, predict what will happen, choose a response, and execute the maneuver. Traditional challenges already encountered at low speeds become exacerbated when the AV is moving at high speed.

The present study sheds light on the challenges associated with the prospective deployment of autonomous vehicles (AVs) at high-speed road corridors. The study accomplishes this by assessing regulatory and safety frameworks and developing insights inferred from published literature which in some cases include documented evidence of the lessons learned from autonomous racing events. These assessments and insights, which can support policies that could promote safe operations and effective human-machine (operator-AV) interfaces at high speeds, were done from the perspective of the AV functional modules and HMI aspects.

Regarding AV operational modules, the study addressed perception and sensing, localization and mapping, prediction and situation awareness, path planning, vehicle control, and compute resources at high speed. Perception challenges at high speed include detecting hazards at sufficient distance, recognizing stationary objects, dealing with occlusion, operating in poor visibility, handling rapid changes in the scene, identifying unusual situations, and connecting detection to prediction. Localization challenges at high speed include maintaining accurate lane position, estimating heading accurately, handling unreliable satellite positioning, managing outdated maps, keeping the position estimate current, and recognizing uncertainty. Path-planning challenges at high speed include planning farther ahead while predictions become less certain, evaluating gaps using relative speed, generating physically feasible trajectories, choosing between braking and steering, and avoiding unstable decision changes, and preserving a fallback. At high speed, control challenges include greater sensitivity to steering inputs, changing tire-road friction, coordinating braking and steering, accounting for actuator limits and delay, responding to disturbances, and maintaining comfort without sacrificing safety.

Regarding the HMI challenges at high speeds, these include clarification of the driver's role, preventing comprehension confusion among the modes, rebuilding situational awareness in events of disruptions or prolonged inattention, designing HMI systems that provide adequate takeover time, separating the concepts of response speed from response quality, designing warnings that convey urgency and attract driver's attention without startle, providing useful context without overloading the driver, monitoring driver readiness, and transferring control smoothly, and managing a failed takeover.

From the review of past work in this report, it can be propounded that the AV module-related operational limitations and HMI challenges at high speed are interdependent in at least three ways. First, they converge on the same underlying issue: the required look-ahead distance, prediction horizon, information volume, and consequence severity all scale upward sharply at higher speeds. Second, the technical difficulties associated with the functional modules propagate directly into HMI difficulty. Third, compute/latency challenges seem to limit what HMI can even attempt: there is proportionally less compute budget left over for the HMI functions.

In the emerging era of autonomous mobility, high speed roads (national highways, interstates, and other freeways and expressways) will continue to play their critical role of mobility within the panorama of road classes and their functional roles (accessibility on one extreme of this panorama and mobility on the other). Improvements to the AV modules and HMI interactions can help high-speed roads play their key role of mobility in a manner that provides opportunities to mitigate traffic congestion, reduce collisions, and save energy, for both personal (individual) AVs and AV fleets operating in specific road corridors or networks. As more companies operate automated logistics fleets, the urban logistics operations ideas presented in these studies will be manifest further in all urban road contexts.

4.2 Recommendations

To mitigate the challenges encountered by AVs at high-speed road sections, we present herewith a few recommendations (as summarized in Figure 12), and we identify the stakeholder (actor) responsible for considering/implementing the recommendation. Most of these recommendations are related to the AV functional modules, with one related to HMI.

1. *Road infrastructure standards*. Where AVs are to be deployed at high-speed sections, this should initially happen at sections with tightly constrained ODDs, until more advanced technology is developed and sufficient knowledge and experience are gained to permit deployment at other high-speed sections. The initial sections for deployment should have geofenced corridors with well-maintained lane markings, consistent geometric design throughout the section length. AV operations in sections with poor lighting should be restricted, particularly during inclement weather, fog, smoke, and other extreme environmental conditions, enforced using variable message signs and warnings conveyed by traffic control centers to AVs through in-vehicle information systems. (Actor: IOOs).

2. *Sensor standards*. For AV operations on high-speed road sections, the number of perception modes (sensor types), with quality standards for each sensor type specified by regulation agencies should be featured in the AV. These standards, which are expected to change over the years as perception technology advances, could include robust sensor performance under specific minimum levels of environmental adversity (rain, fog, snow, poor pavement condition, low retro-reflectivity, etc.). OEMs should abide by the minimum regulator-specified hardware/software capabilities of in all modules including data fusion from multiple sensor modes. (Actor: OEMs).

3. *Cyber infrastructure standards*. Cooperative perception (V2I/V2X) and roadside sensing and communication on the high-speed corridor slated for AV for deployment should be provided. This can help reduce occlusion- and range-limited sensing adversities that trigger disengagement of the automated system. (Actor: IOOs).

4. *Safety validation*. Due to the infeasibility of meeting the extreme statistical limits for safety validation, scenario-based and simulation validation (not the number of miles driven by AVs at high-speed sections) could be adopted as the primary approach for evaluating AV safety at high-speed roads. In evaluating real-life crashes, high-speed safety performance data should be considered rather than urban (relatively low speed) road data. (Actor: NHTSA).

5. *Seamless and efficient integration of ADS components.* Kinetic energy increases significantly with speed (from 56 to 130 km/h, kinetic energy rises 5.4 times). Therefore, at higher speeds, even a millisecond of latency could result in serious damage if the several yards of unguided travel caused misdirection and collision, signifying that ultra-low latency is critical for safety and control. To address latency constraints, system designers could adopt conservative tuning of the automated system. Overall, for safe and reliable AV deployment at high-speed road sections, there must be prior demonstration of seamless, efficient integration of components and sub-systems that span physical, digital, psychological, and regulatory domains. (Actors: IOOs and OEMs).

6. *Human-centered systems.* AVs potentially provide a more inclusive transportation mode to the general population including travelers that are unable to drive, including the disabled, elderly, and children. Studies must be carried out to investigate how such travelers would interact with the HMI and/or trust these autonomous systems, even at low speeds. At high speed, the stakes are higher, as more risk is involved. In this respect, there are two classes of recommendations (based mostly on NTSB insights gained after crashes involving AVs operating at high speed):

6A: Implementation of NTSB's requirement of vehicle manufacturers to deploy "partial vehicle automation systems that address known system limitations," including: integrating and concurrently engaging AEB or other safety-critical technologies (active intelligent speed assistance, driver monitoring); promoting driver engagement through targeted design, lowering safety risks posed by automation misuse or complacency, and establishing "maximum operational speeds for automation systems based on their overall capabilities (Actor: USDOT, OEMs).

6B: Implementation of NTSB's recommendation that NHTSA should require manufacturers should equip eligible vehicles (that is, new SAE International Level 2-capable passenger vehicles) with (a) telematic capability to provide crash notification to the manufacturer; (b) ability to record specific data related to these systems, including, (i) system availability, (ii) driver alerts, (iii) system engagement and activation denial, and (iv) system faults for driver monitoring, AEB, lane centering, forward collision warning, lane departure prevention; and (c) driver monitoring systems (DMS) capable of minimizing driver inattention, automation complacency, and misuse of vehicle automation by providing warnings about accumulated short glances over a prolonged period and differentiating genuine on-road glances from attention directed to objects. (Actor: NHTSA, OEMs).

6C: Implementation of NTSB recommendation to vehicle manufacturers to ensure/revise DMS to provide the capability to (a) detect/disseminate warnings regarding cumulative short distractions (of the driver) over a prolonged period, (b) distinguish between dutiful driver on-road glances vs. errant glances; (c) and "issue initial and subsequent multi-modal alerts" at frequencies that reduce

the propensity and duration of eyes-off-road situations, (d) modify ADS to require that appropriate AEB engagement; and that appropriate speed tolerances are established to reduce instances of excessive speeding, considering complexity of ambient traffic and roadway environment, and the system's operational capabilities. (Actor: OEMs).

6D: OEMs and relevant stakeholders should work together to establish thresholds regarding takeover lead time, initiation of driver monitoring and initiation of countermeasures where a concern arises, and speed limits for automation. (Actor: OEMs, NHTSA, IOOs).

7. *System-of-systems considerations.* High-speed road sections could pose a barrier to widespread AV deployment due to the higher propensity of severe casualty when a high-speed vehicle encounters a crash. AV deployment at high-speed sections must be coupled with progressive legislative and standard-setting efforts. By shifting the legal focus from human-centric physical vehicle controls to algorithm-centric safety validation and continuous data reporting may be a way for regulators to promote innovative vehicle designs. Continuous and harmonious integration of vehicle engineering, infrastructure readiness, human psychology, and adaptive public policy. (Actors: IOOs, OEMs, NHTSA, and policymakers).

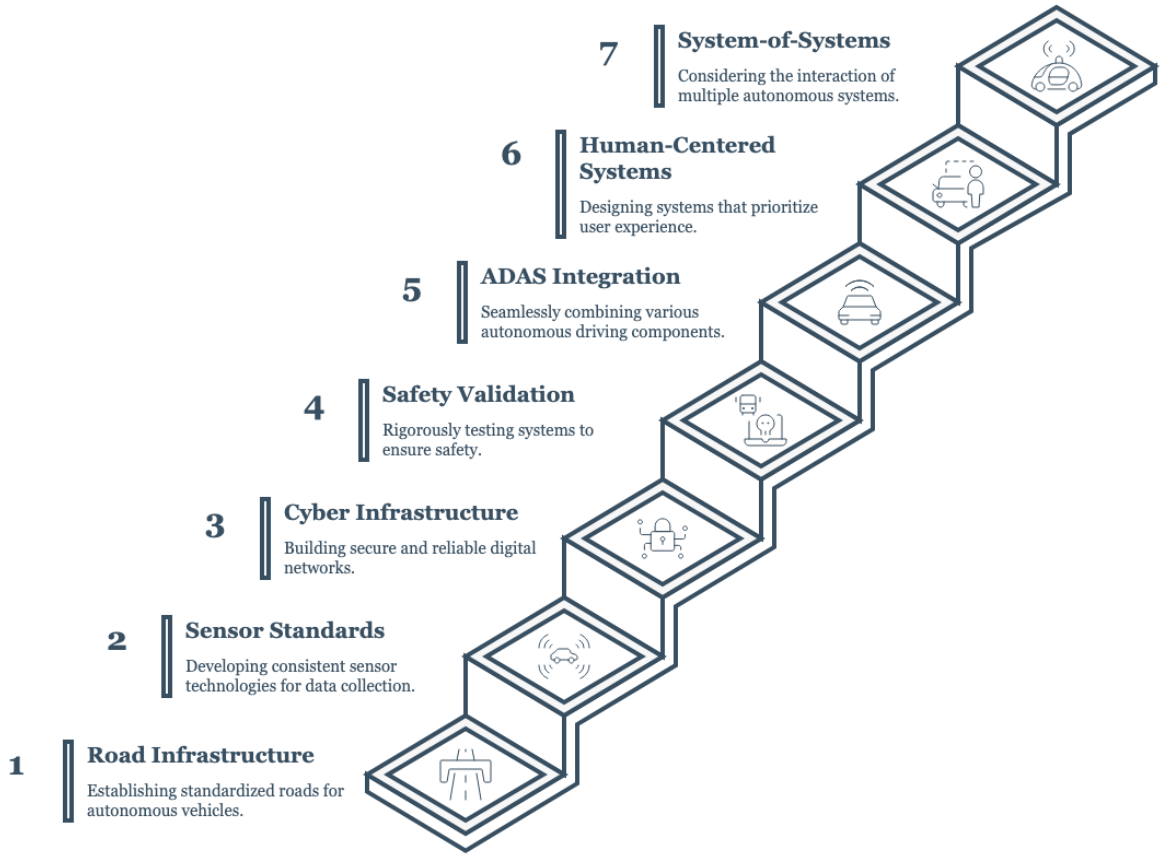


Figure 12. AV operations at high-speed roads – Some recommendations.

The actors in all the above recommendations will also include academic researchers who carry out research in the various AV functional modules and in HMI issues in autonomous driving and provide data-driven evidence that will be considered by the IOOs, OEMs, policymakers, and other implementors. Researchers in AV functional modules include those who use simulation platforms and real-life platforms including autonomous racecars. These recommendations could help inform AV module and HMI design, AV-cognizant infrastructure design and management, and AV-related policymaking to support AV operations at high-speed public roads. Implementing them will require a sustained collaborative effort among the stakeholders of autonomous mobility.

4.3 Caveats on Transferability

The racetrack experiences identified in this report – experiential, anecdotal, documented in the cited research literature – provide information that could be helpful towards the design of AV modules and the development physical and cyber infrastructure to support AV operations, thereby helping to promote safe and efficient AV operations on freeways and other high-speed road corridors. Many of the insights on the AV modules (regarding latency, vibration, sensing range in particular) gained on the racetrack can be transferable to high-speed public road operations. However, there are a few caveats that highlight the limitations on transferability of some of these insights. These limitations arise from the differences in the guideway, vehicle design and dynamics, guideway access, vehicle class distribution (mix of HDV and AV), and cyber infrastructure. Because of these differences, the applicability of any AV module insights gained from AV racing to AV real-world (public roads) operations must be done with caution.

4.4 Avenues for Future Research

The limitations of this study include the use of grey literature, author involvement in events that generated some of the insights, anecdotal observations, company-authored safety data, and fast-moving deployments. There are several avenues for future research regarding AV operational issues and HMI challenges at high-speed road sections. These include the greater use of published academic research, solicitation (through questionnaire surveys and structured interviews) of other individuals that participate in the autonomous racing events, stronger justification for the use of anecdotal observations, verification of company-authored safety data, and collaboration with the industry to keep abreast of fast-moving deployments by companies involved in autonomous driving operations on public roads.

Another avenue for research is the investigation of possible synergies (or at least, interactions) not only between the AV functional modules and HMI aspects but also among their constituent considerations (see Tables 2 and 3 of this report). The functional modules or the HMI aspects may not be independent but interacting holistically to produce some outcome (safety, mobility) and therefore could be investigated in a holistic rather than separate manner. Future work could quantify the consequences of the challenges associated with each AV module and HMI aspect at high speed and ascertain the additivity nature (super-additive, sub-additive, or neutral) of these relationships. This could be done for both mobility and safety outcomes separately. Also, future studies could address insights related to fusion challenges at high speed include synchronizing measurements, aligning coordinate systems, matching observations to the correct object, resolving disagreement, recognizing shared failure causes, and greater management of

information from sources external of the AV.

Regarding human-machine interaction at high-speed road sections, there is already a plethora of ongoing research in various HMI areas: takeover readiness and takeover quality, context-adaptive takeover strategies (at planned freeway exits, work zones, lead-vehicle cut-outs, and suddenly visible stationary objects), fusion of driver's relevant attributes (gaze, head pose, hand readiness, seat position, and system-state interpretation). Other areas include consideration of user profile diversity in comprehensive assessment of takeover readiness, training and communication as part of driver training, and moving beyond simulators, closed tracks, or narrowly controlled public-road studies to test at real life high-speed road sections. It is suggested to continue supporting work in these research areas albeit with priority towards high-speed road sections, as such sections can be considered generally more safety-critical compared to their low-speed counterparts.

Future research could also address a more systematic data collection at racetracks, regarding participants' experiences related to the AV functional modules. Such data collection could range from a simple log of teams' experiences to structured questionnaire surveys and interviews of race team leaders and members and race organizers. These instruments could target the race conditions, team challenges, solutions attempted and the successful ones, regarding localization, sensing, path planning, controls, and data fusion, and other AV modules. Regarding HMI challenges, cab driving simulators equipped with eye trackers, electroencephalogram, electrocardiogram and surveys could be used to measure human drivers' psychological and physiological states, perceptions, attitudes, actions (or inactions) at high speed of the AV, in various simulated conditions of the natural environment and the traffic stream. Even more interestingly, if the driving simulator features AV sensors that operate outside of the driving code, the interactions between HMI aspects and AV modules could be investigated for their super-additivity or sub-additivity.

CHAPTER 5. SYNOPSIS OF PERFORMANCE INDICATORS

5.1 Part I of USDOT Performance Indicators

Over the course of this project's study period, four (4) transportation-related undergraduate courses offered annually and one (1) transportation-related graduate course offered in Fall 2024, that were taught or co-taught by the PI, in the Lyles School of Civil Engineering and the College of Engineering's vertical integrated projects (VIP) initiative at Purdue University. In addition, this research project's CCAT grant funds partially supported one (1) transportation-related Ph.D. program, one (1) transportation-related M.S. program, four transportation-related B.S. programs (civil engineering, electrical and computer engineering, and technology, and computer science). The funds partially supported three (3) graduate students and nine (9) undergraduate students in these programs.

5.2 Part II of USDOT Performance Indicators

Research Performance Indicators:
One (1) journal publication, one (1) conference paper publication, and one (1) conference presentation were produced from this project and related independent projects. Through events including conference presentations and seminars, the findings and methods of this research project were disseminated to approximately 120 event attendees (government, from industry, and academia).

Leadership Development Performance Indicators:
This research project generated or participated in 12 engagement events that were both academic and industry related: NGTS 2024-6, AKS 2024-6, IAC 2024, RoboRacer 2026 Detroit and 2026 Pittsburgh, and AIMM-ICC 2024-2026. The PI holds leadership positions in two international organizations that address issues related to this research project: American Society of Civil Engineers (ASCE) and International Road Federation (IRF).

Education and Workforce Development Performance Indicators:
The lessons from this project were incorporated in the syllabi for the Spring 2024-2026 and Fall 2024-2026 versions of the following Purdue University courses:

(a) Three (3) new vertically-integrated project (VIP) courses within the ambit of Purdue University's College of Engineering (an average of 15 students at each course offering):
Autonomous Race-Engineering Systems (ARES),
Autonomous Motorsports Purdue (AMP), and
Autonomous AI Maritime Maneuvers (AIMM):
See Appendix 2 for details. Students are vertically distributed across all levels (freshman, sophomore, junior, and senior).

(b) Introduction to Civil Engineering Systems (CE 398): a mandatory undergraduate-level course at Purdue University's civil engineering program (an average of 85 students at each course offering). Students are mostly at junior level (3rd year).

(c) CE 597: Emerging Transportation Technologies, a grad-level course in Purdue University, an average 8 students at each course offering. Fall 2024 only. The students are all graduate students.

Some of the students that took these courses have already entered the workforce. Others will soon be entering the workforce, academia and industry. The study increased the number of individuals who were taught to acquire knowledge, use at least some of the technologies created in this research, and apply them when they entered their jobs. Future iterations of the aforementioned courses will also use the methodologies, data, and/or findings from this study.

The project also supported students' participation in several autonomous racing events directly related to the CCAT project: (a) **Indy Autonomous Challenge** (IAC) in Las Vegas, 2023 and 2024, where university teams from around the world competed with their fully autonomous vehicles (see Section 2.2 and Appendix 3 of this report), The Purdue University team name was Black and Gold (renamed Purdue AI Racing in 2024). (b) **Artificial Intelligence Maritime Maneuver Indiana Collegiate Challenge** (AIMM ICC) sponsored by the US Navy, in Angola, Indiana, in 2024, 2025, and 2026, where students from universities in Indiana competed in various mission sets (supply delivery, stealth runs, target location, interception, and rescue). The Purdue University team name is Roboat. (c) **Autonomous Karting Series** (AKS), in West Lafayette in 2024-2026, where university student clubs participated in collegiate competitions where they designed, built, and raced their autonomous go-karts, pushing the limits of robotics and self-driving technology, The Purdue University team name is Autonomous Motorsports Purdue (AMP). (d) the **RoboRacer Autonomous Racing Competitions** at the IEEE Intelligent Vehicles Symposium (IEEE IV 2026) in Detroit, MI in June 2026; and at the IROS 2026 conference in Pittsburgh, PA, in September 2026, where students operated their open-source race cars at one-tenth scale at the largest robotics conferences in the world. The Purdue University team name is Boiler Autonomy.

The CCAT support for these projects occurred in various forms: the project PI spent time advising the teams, administratively (as a faculty advisor) and technically (through technical meetings). Also, the CCAT lab facilities and premises were made available for teams' lab work and field test runs. The support was also financial: CCAT funds were used to partially support team logistics for the competition, for example, purchase of general supplies and minor equipment, payment of race-track fees, and team travel to competition venues and accommodation. Further, three of the graduate students partially funded from the project provided valuable technical support to the teams either as team members or as team advisors.

The outputs, outcomes, and impacts are described in Chapter 6.

CHAPTER 6. STUDY OUTCOMES AND OUTPUTS

6.1 Outputs

6.1.1 Publications, conference papers, or presentations

(a) Publications

1. Ha, Y.J., Filipovska, M., Chen, S., & Labi, S. (2025). Autonomous vehicle fleet operations with constrained entropy-based dynamic autonomous vehicle routing: Insights for environmentally conscious shared mobility. Multimodal Transportation, 5(1), 100236 https://doi.org/10.1016/j.multra.2025.100236

(b) Conference papers

1. Hu, C., Chen, S., Labi, S., Ding, H., Chung, H., Chen, T. (2025). Supplemental taxonomy for SAE L3-L4: A tri-layer environmental grading framework, 2025 IEEE 28th International Conference on Intelligent Transportation Systems (ITSC), DOI:10.1109/ITSC60802.2025.11423080

(c) Conference Presentations

1. Fasate, J., Labi, S. (2025). Adaptive sensor fusion for autonomous driving: A DGConv-based approach, International Conference on Transportation & Development (ICTD 2025), June 8-11, Glendale, AZ.

6.1.2 Other outputs

(a) Editorial of a Special Issue of Fundamental Research Journal:

Huang, J., Labi, S., Kulcsar, B.A., Monreal, C.O., Wu, F., He, Z., Qu, X. (2024). "Editorial: Intelligent vehicles and smart transportation," Fundamental Research, 4(5), 979–980. doi: 10.1016/j.fmre.2024.08.004

(b) The research outcome (documentation of the lessons learned from AV racing) is being used in Purdue University's undergraduate courses (see Appendix 2) and graduate courses related to autonomous transportation:

Emerging Transportation Technologies: Automated, Connected, Shared, Electric, Airborne (CE 597)
Autonomous Race-Engineering Systems (VIP ARES)
Autonomous AI Maritime Maneuvers (VIP AIMM)
Autonomous Motorsports Purdue (VIP AMP)
Civil Engineering Systems (CE 398)

(c) Collaboration Partners:

Motorsports Consulting: Danny White
Boiler Autonomy: Professor Lingxi Li, Purdue University Indianapolis
US Navy and Artificial Intelligence Maritime Maneuver Indiana Collegiate Challenge (AIMM-ICC): Brittany Newell, Tim Murphy, Jason Thume, Amy Ruggles.
Autonomous Karting Series (AKS): Andrew Goeden
Purdue AI Racing: Dan Williams and Team

6.2 Outcomes

The outcomes of this project may have an impact on how well road agencies prepare their transportation infrastructure, particularly high-speed road sections such as freeways and expressways, in preparation towards an emerging era of autonomous mobility. In the areas of AV functional modules (including sensing and perception, localization, path planning and decision making, and control) and human-machine interaction aspects, the study can help road agencies and road policy makers adopt road designs and AV-use regulations that maximize safety and travel efficiency. The findings can also support broader public sector and private sector initiatives related to workforce development, public knowledge and user trust in automation, traffic protocols, standardization of autonomous system components, and certifications. No patents have been filed for the research outcomes.

6.3 List of impacts

This project's results can help support awareness of autonomous driving challenges at high-speed road sections (freeways and expressways), regarding the various AV functional modules and human-machine interactions. Increased user confidence in automation, fewer fatalities, and improved travel efficiency are some examples of how these effects may show up in the transportation system or in society at large. The results of the research can contribute to the body of knowledge on autonomous mobility technologies, broaden the pool of individuals who have received training in autonomous mobility, and enhance the institutional, information, and physical resources related to preparations for an autonomous mobility future. The following are a few impacts of this study:

- The study results impact road user advocates, regulators, IOOs and OEMs because it had provided them stronger justification to collaborate to enhance regulations, and to address challenges posed by AV operations at high-speed road sections
- The study results impact IOOs and OEMs because it has provided them with higher motivation for (a) OEMs to make physical and cyber infrastructure investments (b) OEMs to design enhanced HMIs, to address the identified challenges associated with high-speed operations. This can benefit society through the dimensions of social (reduced crashes), economic (enhanced travel efficiency), and environmental (reduced congestion, and thus, lower fuel use and emissions).
- The study has had some impact on workforce development. Graduate and undergraduate students who worked on this project have started entering the workforce where they are supporting the development of autonomous transportation. One of the students who worked on this project interned at Tesla, Inc., in Summer 2026.
- The project impacted education, as some of the research data and material were incorporated into one graduate course and four undergraduate courses at Purdue University. This transfer of knowledge helped to increase the quality and size of the potential workforce and is expected to ultimately contribute to social and economic development.

REFERENCES

A2RL (2026). What is A2RL? https://a2rl.io/

AASHTO. (2017). Infrastructure needs for autonomous vehicles. Accessed May 16, 2025. https://www.tam-portal.com/project/infrastructure-needs-for-autonomous-vehicles/.

AASHTO (2018). A policy on geometric design of highways and streets, 7th Ed., American Association of State Highway and Transportation Officials, Washington, DC.

Ahnan, M., and Yun, D. (2026). Autonomous Vehicle mode shift's effect on traffic efficiency: A comparison of dedicated lane and mixed traffic approaches. Applied Sciences, 16(15), 7688. https://doi.org/10.3390/app16157688

AKS (2026). Collegiate competition series. https://www.autonomouskartingseries.com/

Alam, M. Z., Kaleem, Z., and Kelouwani, S. (2024). Glare mitigation for enhanced autonomous vehicle perception,in IEEE Transactions on Intelligent Vehicles, 9(11), 7030-7044.

Aldana-López, R., Aragüés, R., and Sagüés, C. (2023). Latency vs precision: Stability preserving perception scheduling, Automatica, 155, 111123.

Alharbi, M., and Karimi, H. A. (2021). Context-aware sensor uncertainty estimation for autonomous vehicles. Vehicles, 3(4), 721-735. https://doi.org/10.3390/vehicles3040042

Ambrosius, E. (2018). Governance and infrastructure for smart and autonomous mobility, IRF & UNECE ITS Event, United Nations, Geneva, Switzerland.

Anne, V. S. R., Einat, T., and Peeta, S. (2022). Using driving simulator environment to determine interactions between user behavior and infrastructure design under autonomous vehicles, Center for Connected & Automated Transportation, Purdue Univ., W. Lafayette, IN.

Appolloni, A., and Caramia, M. (2026). An optimization framework for automated and human-operated fleet routing. Int. J. ITS Res. doi.org/10.1007/s13177-026-00715-9

Aurora Innovation (2025). Aurora expands driverless trucking service from Fort Worth to El Paso, Aurora Innovation, Inc., https://ir.aurora.tech/news-events/press-releases/detail/128/aurora-expands-driverless-trucking-service-from-fort-worth-to-el-paso

Autosport. (2025). A2RL to return for Season Two at Yas Marina Circuit. www.autosport.com/general/news/a2rl-to-return-for-season-two-at-yas-marina-circuit/10724680/

Babic, D., Babic, D., Fiolic, M., Eichberger, A., and Magosi, Z.F. (2022). Impact of road marking retroreflectivity on machine vision in dry conditions: On-road test. Sensors (Basel), 22(4),1303. doi: 10.3390/s22041303.

Bellairs, R. (2019). Why SOTIF (ISO/PAS 21448) is key for safety in autonomous driving, Perforce Software, accessed on June 13, 2026, https://www.perforce.com/blog/qac/sotif-iso-pas-21448-autonomous-driving

Betz, J., Zheng, H., Liniger, A., Rosolia, U., Karle, P., Behl, M., Krovi, V., and Mangharam, R. (2022). Autonomous vehicles on the edge: A survey on autonomous vehicle racing, IEEE Open Journal of Intelligent Transportation Systems, 3, 458-488.

Betz, J., Betz, T., Fent, F., Geisslinger, M., Heilmeier, A., Hermansdorfer, L., Herrmann, T., Huch, S., Karle, P., Lienkamp, M., Lohmann, B., Nobis, F., Ögretmen, L., Rowold, M., Sauerbeck, F., Stahl, T., Trauth, R., Werner, F., and Wischnewski, A. (2023). TUM autonomous motorsport: An autonomous racing software for the Indy Autonomous Challenge. Journal of Field Robotics. 40 (4), 783-809. https://doi.org/10.1002/rob.22153

Betz, T., Karle, P., Werner, F., and Betz, J. (2023). An analysis of software latency for a high-speed autonomous race car—A case study in the Indy Autonomous Challenge, SAE Int. J. CAV 6(3), 283-296, 2023, https://doi.org/10.4271/12-06-03-0018.

Bianconi, S., Ribes-Pleguezuelo, P. and Silvestri, F. (2025). Requirements for next-generation integrated photonic FMCW LiDAR sources. Nat Commun 16, 6739 doi.org/10.1038/s41467-025-62027-y

Butilă, E. V., Voinea, G.-D., Boboc, R. G., and Ambrosi, G. (2026). Autonomous vehicles in the traffic

ecosystem: A comprehensive review of integration, impacts, and policy implications. Vehicles, 8(2), 41. https://doi.org/10.3390/vehicles8020041
California Department of Motor Vehicles. (2025). 2024 autonomous vehicle disengagement reports. https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/disengagement-reports/
Capallera, M., Angelini, L., Meteier, Q., Khaled, O. A., and Mugellini, E. (2023). Human-vehicle interaction to support driver's situation awareness in automated vehicles: A systematic review, IEEE Transactions on Intelligent Vehicles, 8(3), 2551-2567.
Carnegie Mellon University. (2020). New perception metric balances reaction time, accuracy. School of Computer Science. https://www.cs.cmu.edu/news/2020/new-perception-metric-balances-reaction-time-accuracy
Casas, S., Sadat, A., and Urtasun, R. (2021). MP3: A unified model to map, perceive, predict and plan. arXiv. https://arxiv.org/abs/2101.06806
Chang, Q., and Chen, H. (2025). Impacts of autonomous vehicles on freeway with conditional isolated and dedicated lanes. Sci Rep. 15(1), 21374. doi: 10.1038/s41598-025-06735-x
Charles, I., Maghsoumi, H., and Fallah, Y. (2025). Advancing autonomous racing: A comprehensive survey of the Roboracer (F1-TENTH) Platform. 2025 6th International Conference on Artificial Intelligence, Robotics and Control (AIRC), 207-213.
Chalvatzaras, A., Pratikakis, I., and Amanatiadis, A. A. (2022). A survey on map-based localization techniques for autonomous vehicles. IEEE Transactions on intelligent vehicles, 8, 1574–1596.
Cheng, Z., Zhu, J., Feng, Z., Yang, M., Zhang, W., and Chen, J. (2025). Driving safety risk analysis and assessment in a mixed driving environment of connected and non-connected vehicles: A systematic survey. IEEE transactions on intelligent transportation systems, 26(5), 5747-5781.
Chityala, S., Sobanjo, J. O., Erman Ozguven, E., Sando, T., and Twumasi-Boakye, R. (2020). Driver behavior at a freeway merge to mixed traffic of conventional and connected autonomous vehicles. Transportation Research Record 2674(11), 867-874.
CNBC (2025). Robotaxis in 2025: Waymo plots global expansion as Zoox, Tesla roll to the starting line, www.cnbc.com/2025/12/16/waymo-amazon-zoox-tesla-robotaxi-expansion.html
Cui, G., Zhang, W., Xiao, Y., Yao, L., and Fang, Z. (2022). Cooperative perception technology of autonomous driving in the internet of vehicles environment: A review. Sensors, 22(15), 5535.
Dabeer, O., Ding, W., Gowaiker, R., Grzechnik, S.K., Lakshman, M. J., Lee, S., Reitmayr, G., Sharma, A., Somasundaram, K., Sukhavasi, R.T., Wu, X. (2017). An end-to-end system for crowdsourced 3D Maps for autonomous vehicles: The mapping component, Procs., 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), September 24–28, 2017, Vancouver, BC, Canada.
Dallas Innovates (2025). Aurora begins nighttime driverless truck runs between Dallas and Houston, dallasinnovates.com/aurora-begins-nighttime-driverless-truck-runs-between-dallas-and-houston/
DARPA (2014). The DARPA grand challenge: Ten years later, https://www.darpa.mil/news/2014/grand-challenge-ten-years-later
de Sio, F.S., Mecacci, G., Calvert, S., Heikoop, D., Hagenzieker, M., van Arem, B. (2022). Realizing meaningful human control over automated driving systems: A multidisciplinary approach. Minds Mach (Dordr). 1-25. doi: 10.1007/s11023-022-09608-8.
Deans, A., Guy, I., Gupta, B., Jamal, O., Seidl, M., and Hynd, D. (2025). Status of driver state monitoring technologies and validation methods, Driver and Vehicle Standards Agency (DVSA), Project Nr. PPR2068, TRL Limited, UK.
Demeter, Z., Hell, M., and Hajgató, G. (2024). Lessons learned from an autonomous race car competition. Engineering Proceedings, 79(1), 25.
Deng, M., Gluck, A., Menassa, C., Kamat, V., Li, D., and Brinkley, J. (2024). Predicting driver takeover performance in conditional automation (level 3) through physiological sensing, CCAT,

University of Michigan, Ann Arbor, MI.
Denoyelle, L., Hamouche, R., Kocik, R., Dokladalova, E., and Hautière, N. (2025). Review of autonomous racing competitions and technologies. FAST-zero'25, Université Gustave Eiffel, Arles, France.
Dong, J., Du, R., Ha, Y.J., Chen, S., and Labi, S. (2022). Development of AI-based and control-based systems for safe and efficient operations of connected and autonomous vehicles, CCAT Report #41, The Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.
Dong, J., Chen, S., and Labi, S. (2023). Promoting CAV deployment by enhancing the perception phase of autonomous driving using explainable AI, CCAT Report #74, The Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.
Dong, X., Cappuccio, M., Alnajjar, F., Ali, L., Al Jassmi, H., Debie, E., Ghasrikhouzani, M., Lanteri, A., McGregor, T., Molloy, O., Plebe, A., Regan, M., Sandoval, E., and Zhang, D. (2026). Why autonomous vehicles are not ready yet: A multi-disciplinary review of problems, attempted solutions, and future directions. Journal of Field Robotics 43, 2254–2341.
Du, R., Ha, P.Y.J., Dong, J., Chen, S., and Labi, S. (2022). Large network multi-level control for CAV and smart infrastructure: AI-based fog-cloud collaboration, CCAT Report #55, The Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.
Eriksson, A., and Stanton, N. A. (2017). Takeover time in highly automated vehicles: Noncritical transitions to and from manual control. Human Factors: The Journal of the Human Factors and Ergonomics Society, 59(4), 689-705.
Esmaeeli, H., Mazaheri, A., Mohammadi Ghohaki, T., and Alecsandru, C. (2025). Evaluating autonomous vehicle safety countermeasures in freeways under sun glare. Future Transportation, 5(1), 20.
Fasate, J., and Labi, S. (2025). Adaptive sensor fusion for autonomous driving: A DGConv-based approach, International Conference on Transportation & Development (ICTD 2025), June 8-11, Glendale, AZ.
Favero, R., and Setti, J. R. (2024). Factors affecting the impact of autonomous vehicles on freeway operations–an exploratory analysis using pces. Promet-Traffic&Transportation, 36(1), 55-68.
Feng, Y., Bao, S., and Liu, H. (2023). CAV testing scenario design and implementation using naturalistic driving data and augmented reality, Center for Connected & Automated Transportation, University of Michigan, Ann Arbor, MI.
Feng, Y., and Liu, H. (2019). Development of an augmented reality environment for connected and automated vehicle testing, Center for Connected & Automated Transportation, University of Michigan, Ann Arbor, MI.
Feng, Y., and Tarko, A. (2023). Development of a cooperative perception system, CCAT Report No. 70, Center for Connected & Automated Transportation, Purdue University, W. Lafayette, IN.
FHWA (2025). Automated vehicle activities and resources, Federal Highway Administration, Washington, DC, https://highways.dot.gov/automation
Formosa, N., Quddus, M., Man, C.K., Singh, M.K., Morton, C., and Masera, C.B. (2024). Evaluating the impact of lane marking quality on the operation of autonomous vehicles, Journal of Transportation Engineering, Part A: Systems, 150(1), doi.org/10.1061/JTEPBS.TEENG-7688
Fu, S., Yang, Z., Ma, Y., Li, Z., Xu, L., and Zhou, H. (2024). Advancements in the intelligent detection of driver fatigue and distraction: A comprehensive review. Applied Sciences. 14. 3016. 10.3390/app14073016.
Gan, Y.J., and Labi, S. (2026). High-speed driverless racing: Lessons for autonomous mobility, CCAT Report #115, The Center for Connected & Automated Transportation, Purdue University, W. Lafayette, IN.
Gehrig, D., and Scaramuzza, D. (2024). Low-latency automotive vision with event cameras. Nature,

629(8014), 1034-1040.
Ghilotti, F., Palladin, E., Brucker, S., Sigal, A., Bijelic, M., and Heide, F. (2026). TruckDrive: Long-range autonomous highway driving dataset, https://arxiv.org/abs/2603.02413
Global Formula Racing (2025). Formula Student, https://www.global-formula-racing.com/en/ accessed on December 17, 2025.
Gold, C., Dambock, D., Lorenz, L., and Bengler, K. (2013). "Take over!" How long does it take to get the driver back into the loop? Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 57(1), 1938–1942. http://doi.org/10.1177/1541931213571433
Gold, C., Korber, M., Lechner, D., and Bengler, K. (2016). Taking over control from highly automated vehicles in complex traffic situations: The role of traffic density, Human Factors – The Journal of the Human Factors and Ergonomics Society 58(4), 642-652.
Gong, Z. (2024). Challenges and Opportunities of Automotive HMI. In: Harris, D., Li, WC., Krömker, H. (eds) HCI International 2024 – Late Breaking Papers. HCII 2024. Lecture Notes in Computer Science, vol 15381. Springer, Cham. https://doi.org/10.1007/978-3-031-76824-8_3
Gopalakrishna, D., Carlson, P., Sweatman, P., Raghunathan, D., Brown, L., and Serulle, N. (2021). Impacts of automated vehicles on highway infrastructure. Federal Highway Administration (FHWA)-HRT-21-015, Washington, DC.
Gotlib, D., Gartner, G., and Miksa, K. (2026). HD maps for autonomous vehicles: Implications for cartographic theory and practice. ISPRS International Journal of Geo-Information, 15(2), 68. https://doi.org/10.3390/ijgi15020068
Grobelna, I., Mailland, D., and Horwat, M. (2025). Design of automotive HMI: New challenges in enhancing user experience, safety, and security. Applied Sciences, 15(10), 5572. https://doi.org/10.3390/app15105572
Guan, X., Zhou, H., Zhao, Y., and Zhou, Y. (2024). Emergency vehicle detection in noisy environments based on feature fusion. In 2024 IEEE International Conference on Software System and Information Processing (ICSSIP), 22-25. IEEE, 2024.
Guo, X., Wan, D., Liu, D., Mousas, C., and Chen, Y. (2022). A virtual reality framework to measure psychological and physiological responses of the self-driving car passengers, CCAT, Purdue University, W. Lafayette, IN.
Ha, Y.J., Filipovska, M., Chen, S., and Labi, S. (2025). Autonomous vehicle fleet operations with constrained entropy-based dynamic autonomous vehicle routing: Insights for environmentally conscious shared mobility. Multimodal Transportation, 100236. https://doi.org/10.1016/j.multra.2025.100236
Hau, F., Baumgärtner, F., and Vossiek, M. (2020). The degradation of automotive radar sensor signals caused by vehicle vibrations and other nonlinear movements. Sensors (Basel) 20(21), 6195. doi: 10.3390/s20216195
He, D., Donmez, B. 2022The influence of visual-manual distractions on anticipatory driving. Hum Factors. 64(2), 401-417. doi: 10.1177/0018720820938893
He, H., Gray, J., Cangelosi, A., Meng, Q., McGinnity, T. M., and Mehnen, J. (2022). The challenges and opportunities of human-centered AI for trustworthy robots and autonomous systems, in IEEE Transactions on Cognitive and Developmental Systems, 14(4), 1398-1412.
He, S., Ding, F., Lu, C., Qi, Y. (2022). Impact of connected and autonomous vehicle dedicated lane on the freeway traffic efficiency. Eur. Transp. Res. Rev. 14, 12. https://doi.org/10.1186/s12544-022-00535-4
He, Y., Xiang, D., and Wang, D. (2025). Traffic safety evaluation of emerging mixed traffic flow at freeway merging area considering driving behavior. Scientific Reports 15, 10686. https://doi.org/10.1038/s41598-025-94658-y
Hentati T., Jackson J., and Moldovan, O. (2026). Human-centered design approach for connected, cooperative, and automated mobility: Insights from the CERTAIN and AIGGREGATE projects.

In 28th International Technical Conference on the Enhanced Safety of Vehicles
Herb, M., Weiherer, T., Navab, N., and Tombari, F. (2019). Crowd-sourced semantic edge mapping for autonomous vehicles, 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Macau, China, 2019, 7047-7053, doi:10.1109/IROS40897.2019.8968020.
Hu, C., Chen, S., Labi, S., Ding, H., Chung, H., Chen, T. (2025). Supplemental taxonomy for SAE L3-L4: A tri-layer environmental grading framework, 2025 IEEE 28th International Conference on Intelligent Transportation Systems (ITSC), doi:10.1109/ITSC60802.2025.11423080
Huang, G., and Pitts, B. J. (2022). Takeover requests for automated driving: The effects of signal direction, lead time, and modality on takeover performance. Accid Anal Prev. 165:106534. doi: 10.1016/j.aap.2021.106534.
Huang, J., Labi, S., Kulcsar, B.A., Monreal, C.O., Wu, F., He, Z., Qu, X. (2024). Intelligent vehicles and smart transportation, Editorial, Fundamental Research, 4(5), 979–980. doi: 10.1016/j.fmre.2024.08.004
IAC (2025). Indy Autonomous Challenge, www.indyautonomouschallenge.com/ Accessed 2025-12-06.
Indy Autonomous Challenge. (2026, July 29). Indy Autonomous Challenge returns with head-to-head racing during Grand Prix of Monterey weekend at WeatherTech Raceway Laguna Seca [Press release]. https://www.indyautonomouschallenge.com/laguna-seca-2026
IIHS (2024a). Safeguards for partial driving automation test protocol and rating guidelines Version I, Insurance Institute for Highway Safety, Ruckersville, VA.
IIHS (2024b). First partial driving automation safeguard ratings show industry has work to do, Insurance Institute for Highway Safety, Highway Loss Data Institute, Ruckersville, VA.
ISO (2018). Road vehicles — Functional safety. Part 1: Vocabulary, ISO 26262-1, 2nd Edition.
ISO (2022a). ISO 21448:2022, Road vehicles — Safety of the intended functionality, 1st Edition, www.iso.org/standard/77490.html
ISO (2022b). ISO 34502:2022, Road vehicles — Test scenarios for automated driving systems — Scenario based safety evaluation framework.
ISO (2025). 34505:2025, Road vehicles Test scenarios for automated driving systems — Scenario evaluation and test case generation, https://www.iso.org/standard/78954.html
Jeong, Y., Kim, S., and Yi, K. (2020). Road-aware trajectory prediction for autonomous driving on highways. Sensors, 20(17), 4703. https://doi.org/10.3390/s20174703
Jiang, A. (2021). Research on the development of autonomous race cars and impact on self-driving cars. Journal of Physics: Conference Series, 1824(1), 012009.
Kail, B., Papp, Z., and Fazekas, M. (2024). Localization challenges in autonomous motorsport. Engineering Proceedings, 79(1), 88. doi.org/10.3390/engproc2024079088
Kalaria, D., Lin, Q., and Dolan, J. M. (2022). Delay-aware robust control for safe autonomous driving. 2022 IEEE Intelligent Vehicles Symposium (IV), Aachen, Germany, 1565-1571.
Kalra, N., and Paddock, S. M. (2016). Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability? Transportation Research Part A: Policy and Practice, 94, 182-193.
Kang, J., Hamidi, O., Vanäs, K., Eidevåg, T., Nilsson, E., and Friel, R. (2025). Effects of dust and moisture surface contaminants on automotive radar sensor frequencies. Sensors, 25(7), 2192. https://doi.org/10.3390/s25072192
Karaman, S., Anders, A., Boulet, M., Connor, J., Gregson, K., Guerra, W., Guldner, O., Mohamoud, M., Plancher, B., Shin, R., and Vivilecchia, J. (2017). Project-based, collaborative, algorithmic robotics for high school students: Programming self-driving race cars at MIT. 2017 IEEE Integrated STEM Education Conference (ISEC), 195-203. https://doi.org/10.1109/isecon.2017.7910242.
Karimi, A., Mao, S., Lotto, G., Lee, J.J., and Bassani, M. (2026). Drivers and automation: A systematic review on road suitability for assisted and partially/conditionally automated vehicles,

Transportation Research Interdisciplinary Perspectives, 37, 101986, doi.org/10.1016/j.trip.2026.101986.
Khalil, A., and Bayoumi, A. (2026). PLM-Net: Perception latency mitigation network for vision-based lateral control of autonomous vehicles. Sensors, 26(6), 1798. https://doi.org/10.3390/s26061798
Khan, M. A., Kumar, S., and Rao, P. (2025). Evaluating LiDAR perception algorithms for all-weather autonomy. Sensors, 25(23), 7436. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC12736427/
Kim, M.-J., Yu, S.-H., Kim, T.-H., Kim, J.-U., and Kim, Y.-M. (2021). On the development of autonomous vehicle safety distance by an RSS model based on a variable focus function camera. Sensors, 21(20), 6733. https://doi.org/10.3390/s21206733
Kim, Y., Chung, S.K., and Lee, J. (2025). Acoustic and heat-driven active cleaning technology for optical sensors, Sensors and Actuators A: Physical, 392, 116721, doi.org/10.1016/j.sna.2025.116721.
Koirala, P., and Fleming, C. (2024). F1-Tenth autonomous racing with offline reinforcement learning methods. 2024 IEEE 27th International Conference on Intelligent Transp. Sys., 3922-3929.
Koopman, P., Osyk, B., and Weast, J. (2019). Autonomous vehicles meet the physical world: RSS, variability, uncertainty, and proving safety. In A. Romanovsky, E. Troubitsyna, and F. Bitsch (Eds.), Computer safety, reliability, and security. SAFECOMP 2019 (Lecture Notes in Computer Science 11698, 245-258). Springer. https://doi.org/10.1007/978-3-030-26601-1_17
Kral, W., and Dalpez, S. (2018). Modular sensor cleaning system for autonomous driving. ATZ Worldw 120, 56–59. doi.org/10.1007/s38311-018-0153-1
Kroes, M. (2026). Autonomous vehicles and toll roads: threat, opportunity – or both? How self-driving vehicles could reshape toll road demand and revenue. www.oxfordeconomics.com/resource/autonomous-vehicles-and-toll-roads-threat-opportunity
KTH Formula Student (2025). About KTH Formula Student, https://kthformulastudent.se/about/ accessed on August 15, 2026.
Kusano, K. D., Scanlon, J. M., Chen, Y.-H., McMurry, T. L., Chen, R., Gode, T., and Victor, T. (2024). Comparison of Waymo rider-only crash data to human benchmarks at 7.1 million miles. Traffic Injury Prevention, 25(sup1), S66-S77. https://doi.org/10.1080/15389588.2024.2380786
Kusano, K. D., Scanlon, J. M., Chen, Y.-H., McMurry, T. L., Chen, R., Gode, T., and Victor, T. (2023). Comparison of Waymo rider-only crash data to human benchmarks at 7.1 million miles [Preprint]. arXiv. https://arxiv.org/abs/2312.12675
Labi, S. (2019). Preparing our infrastructure for connected and autonomous vehicle operations, 2019 International Conference on Smart Cities (2019 ICSC), Seoul, July 17–19, 2019, organized by International Society for Maintenance and Rehabilitation of Transport Infrastructures (iSmarti), University of Iowa.Iowa City, IA.
Labi, S., Saeed, T.U., Pourgholamali, M., Saka, Z.A., and Sinha, K.C. (2023). Design and management of highway infrastructure to accommodate CAVs, CCAT Report #29, The Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.
Lee, D., Jung, C., Finazzi, A., Seong, H., and Shim, D. H. (2022). A resilient navigation and path planning system for high-speed autonomous race car. https://arxiv.org/abs/2207.01223
Lee, W., Cho, H., Hyeong, S., and Chung, W. (2023). Empirical analysis of autonomous vehicle's LiDAR detection performance degradation for actual road driving in rain and fog. Sensors, 23(6), 2972. https://doi.org/10.3390/s23062972
Lee, J., Eom, C., Lee, D., and Kwon, M. (2024). Jerk-minimized autonomous driving strategy with deep reinforcement learning, 2nd Workshop on Multi-Agent Dynamic (MAD) Games, 2024 IEEE International Conference on Robotics and Automation (ICRA), May 13, 2024. Yokohama, Japan, https://icra2024-madgames.F1-Tenth.org/papers/lee.pdf
Li, H., De Cristofaro, F., Orucevic, F., Gu, Z., and Eichberger, A. (2023). Comparative analysis of critical lane change for autonomous driving vehicles and human drivers, 44th International Vienna Motor Symposium - Vienna, Wien, Austria, https://wiener-motorensymposium.at/en/

Li, P., Wang, R., Wang, Y., and Tao, W. (2020). Towards streaming perception. arXiv. https://arxiv.org/abs/2005.10420
Li, Y., Sharma, A., John, A.P., Alabi, B.N.T., Chen, S., and Labi, S. (2023). Development of situational awareness enhancing system for manual takeover of AV, CCAT Report #53, The Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN
Li, Z., Li, L., and Huang, J. (2026). Exploiting the benevolent machine: Psychological antecedents of human drivers' strategic exploitation intentions toward autonomous vehicles in mixed traffic, Transportation Research Part F: Traffic Psychology and Behavior, 120, 103616, doi.org/10.1016/j.trf.2026.103616.
Linnhoff, C., Hofrichter, K., Elster, L., Rosenberger, P., and Winner, H. (2022). Measuring the influence of environmental conditions on automotive lidar sensors. Sensors, 22(14), 5266.
Lippold and Vetters, 2014 Design guidelines for motorways and for rural roads in Germany, Rural Roads Design meeting nr 5. April 3-4, 2014, Copenhagen, Denmark. https://nmfv.dk/wp-content/uploads/2014/04/Design-guidelines-for-motorways-and-for-rural-roads-in-Germany-Christian-Lippold-and-Anne-Vetters.pdf
Liu, C.-J., Wang, F.-K., Wang, Z.-Z., Wang, T., and Jiang, Z.-H. (2022). Autonomous vehicles for enhancing expressway capacity: A dynamic perspective. Sustainability, 14(9), 5193.
Liu, H. X., and Feng, Y. (2020). Accelerated training for connected and automated vehicles based on adaptive evaluation method. Technical Report. UMTRI-2023-5. DOI: 10.7302/7017
Liu, H. X., and Feng, Y. (2023). DeepScenario: City scale scenario generation for automated driving system testing & evaluation. Technical Report No. UMTRI-2023-3. DOI: 10.7302/7018
Liu, S. (2020). DARPA: A Global Innovation Differentiator, in IEEE Engineering Management Review, 48(2), 65-71, doi: 10.1109/EMR.2020.2975186
Long, Y., Wei, Y., Zhu, X., and Jie, C. (2024). High-performance formula student autonomous racing car design and prototype test, 9th International Conference on Electronic Technology and Information Science (ICETIS), Hangzhou, China, 2024, 139-143, doi: 10.1109/ICETIS61828.2024.10593991.
Lu, L., Si, G., Liang, X., Li, M., Zhou, F. (2025). A survey on dynamic scene understanding using temporal knowledge graphs: From scene knowledge representation to extrapolation, Neurocomputing, 635, 129854, doi.org/10.1016/j.neucom.2025.129854.
Madane, A. R., and Kuan, H. C. (2025). Real-time high-speed autonomous driving via lidar–event camera fusion using attention-enriched spatio-temporal graph neural networks. Journal of Advances in Signal and Image sciences, 780-793.
Madigan, R., Louw, T. Merat, N. (2018). The effect of varying levels of vehicle automation on drivers' lane changing behavior, PLoS One, 13 (2) (2018), Article e0192190, 10.1371/journal.pone.0192190
Mandalapu, M. K. R. (2025). Real-time AI inference at the edge for self-driving cars. International Journal on Science and Technology, 16(1). https://www.ijsat.org/papers/2025/1/2462.pdf
Manion, P., and Durango-Cohen, P.L. (2025). Optimizing investments in design, maintenance, and operations of transportation infrastructure to capitalize on the promise of connected autonomous vehicles, Technical Report CCAT-NU-2025-2, Northwestern University, Evanston, IL.
Mar, M., Chellapandi, V. P., Yuan, L., Wang Z., and Dietz, E. (2025). Advanced sensor configurations for high-speed autonomous racing vehicles, in IEEE Journal of Selected Areas in Sensors 2, 136-149.
McKinsey (2026). Where to next? Insights from autonomous-vehicle experts. https://www.mckinsey.com/features/mckinsey-center-for-future-mobility/our-insights
Merat, N., Seppelt, B., Louw, T. Engström, J., Lee, J. D., Johansson, E., Green, C. A., Katazaki, S., Monk, C., Itoh, M., McGehee, D., Sunda, T., Unoura, K., Victor, T., Schieben, A., and Keinath, A. (2019). The “Out-of-the-Loop” concept in automated driving: Proposed definition, measures

and implications. Cogn Tech Work 21, 87–98. https://doi.org/10.1007/s10111-018-0525-8
Meuer, K., Kulessa, A., and Fischer, D. (2024). Holistic driver perception—Unaddressed challenges in autonomous driving today. In: Pfeffer, P. (eds) 13th International Munich Chassis Symposium 2022. IMCS 2022. Proceedings. Springer Vieweg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-68160-2_18
Miller, D., Sun, A., Johns, M., Ive, H., Sirkin, D., Aich, S., and Ju, W. (2015). Distraction becomes engagement in automated driving. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 59(1), 1676-1680.
Mirage News (2025). TUM triumphs again at Abu Dhabi autonomous race, Mirage Technology, www.miragenews.com/tum-triumphs-again-at-abu-dhabi-autonomous-race-1571240/
Mohanasundaram, N., and Sai Eshwar Supreet, P. A. (2023). Semi-autonomous miniature car. 2023 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), 1-6.
Molnar, L. J., Zhou, F., Eby, D. W., Zakrajsek, J. S., St. Louis, R., Zanier, N., and Yi, P. (2023). Promoting inclusive design and deployment of connected and automated vehicles for older adults through education and training of engineering students and older drivers, CCAT, University of Michigan, Ann Arbor, MI.
Na, Q., Xie, Q., Zhang, N., Zhang, L., Li, Y., Chen, B., Peng, T., Zuo, G., Zhuang, D., and Song, J. (2023). Optical frequency shifted FMCW Lidar system for unambiguous measurement of distance and velocity, Optics and Lasers in Engineering, 164, 107523, doi.org/10.1016/j.optlaseng.2023.107523.
Nakamoto, N., and Kobayashi, H. (2019). Development of an open-source educational and research platform for autonomous cars. IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society, 6871-6876.
NCSL (2026). Autonomous vehicles legislation database, National Conference of State Legislatures, https://www.ncsl.org/transportation/autonomous-vehicles-legislation-database
Neumeister, D., and Pape, D. (2019). Automated vehicles and adverse weather, Battelle Memorial Institute Tech. Rep. Nr. FHWA-JPO-19-755, prepared for the U.S. Department of Transportation, Washington, DC.
NHTSA (2021). Third Amended Standing General Order 2021-01 – Incident Reporting for Automated Driving Systems (ADS) and Level 2 Advanced Driver Assistance Systems (ADAS), United States National Highway Traffic Safety Administration, US Department of Transportation, Washington, DC. https://www.nhtsa.gov/sites/nhtsa.gov/files/2025-04/third-amended-SGO-2021-01_2025.pdf
NHTSA (2025). Automated vehicle safety, National Highway Transportation Safety Administration, Washington, DC, https://www.nhtsa.gov/vehicle-safety/automated-vehicle-safety
NTSB (2020a). Collision between a sport utility vehicle operating with partial driving automation and a crash attenuator, Mountain View, California, March 23, 2018. Highway Accident Report NTSB/HAR-20/01. Washington, DC.
NTSB. (2020b). Highway accident brief – Collision between car operating with partial driving automation and truck-tractor semitrailer at Delray Beach, Florida, March 1, 2019, National Transportation Safety Board, Washington, DC. https://www.ntsb.gov/investigations/AccidentReports/Reports/HAB2001.pdf
National Transportation Safety Board. (2026a, March 31). Highway investigation report HIR-26-02: Crashes in San Antonio, Texas, and Philadelphia, Pennsylvania, involving vehicles using Ford BlueCruise. https://www.ntsb.gov/investigations/AccidentReports/Reports/HIR2602.pdf
National Transportation Safety Board. (2026b, March 31). NTSB finds automation overreliance contributed to two fatal Ford BlueCruise crashes [Press release]. https://www.ntsb.gov/news/press-releases/Pages/NR20260331.aspx

O'Kelly, M., Zheng, H., Karthik, D., and Mangharam, R. (2020). F1-TENTH: An open-source evaluation environment for continuous control and reinforcement learning. Proceedings of Machine Learning Research, 123, 77–89. https://proceedings.mlr.press/v123/o-kelly20a.html
Ort, T., Paull, L., and Rus, D. (2018). Autonomous vehicle navigation in rural environments without detailed prior maps, 2018 IEEE International Conference on Robotics and Automation (ICRA), Brisbane, QLD, Australia, 2040-2047, doi: 10.1109/ICRA.2018.8460519.
Othman, K. (2021). Impact of autonomous vehicles on the physical infrastructure: Changes and challenges. Designs, 5(3), 40. https://doi.org/10.3390/designs5030040
Papadoulis, A., Quddus, M., and Imprialou, M. (2019). Evaluating the safety impact of connected and autonomous vehicles on motorways. Accident Analysis & Prevention, 124, 12-22.
Paul, N., and Chung, C. (2018). Application of HDR algorithms to solve direct sunlight problems when autonomous vehicles using machine vision systems are driving into sun, Computers in Industry, 98, 192-196.
Peeta, S., Wang, C., Wang, J., Wang, Y., and Zhou, A. (2022). Cooperative control mechanism for platoon formation of connected and autonomous vehicles, CCAT Report #25, Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.
Peng, D., Meijuan, Z., and Ruiqi, W. (2026). Research on vibration control of intelligent suspension for autonomous vehicles. Advances in Mechanical Engineering18(2), doi:10.1177/16878132261420537
Perrone, A. (2025). Innovations from racing that found their way on our roads, Endurance, www.endurancewarranty.com/learning-center/motorsports/
Petersen, L., Robert, L., Yang, X., and Tilbury, D. (2019). Situational awareness, driver's trust in automated driving systems and secondary task performance, SAE Int. J. of CAV, 2(2),129–141, doi:10.4271/12-02-02-0009.
Pipkorn, L., Tivesten, E., and Dozza, M. (2022). It's about time! Earlier take-over requests in automated driving enable safer responses to conflicts. Transportation Research Part F – Traffic Psychology and Behavior, 86(1),196-209.
Pipkorn, L., Tivesten, E., and Dozza, M. (2024). Driver visual attention before and after take-over requests during automated driving on public Roads. Human Factors, 66(2), 336-347.
Purdue University (2026). Lyles CCE hosts 2026 Annual Autonomous Karting Series (AKS) competition, https://engineering.purdue.edu/CCE/AboutUs/News/Transportation
Qiao, Q., Li,H., Cao, Z., and Liu, H. (2025). End2Race: Efficient end-to-end imitation learning for real-time F1-tenth racing, arxiv, https://arxiv.org/html/2509.16894v1
Ramakrishnan, A., Alrajhi, A., Okte, E., Ozer, H., and Al-Qadi, I.L. (2021). Truck-platooning impacts on flexible pavements: Experimental and mechanistic approaches, Technical Report Nr. ICT-21-038). Illinois Center for Transportation, Champaign, IL.
Rangwala, S. (2026). High speed autonomy - From racetrack to highway, https://www.forbes.com/sites/sabbirrangwala/2026/02/17/high-speed-autonomyfrom-racetrack-to-highway/
Reagan, I. J., Teoh, E. R., Cicchino, J. B., Gershon, P., Reimer, B. Mehler, B., and Seppelt, B. (2021). Disengagement from driving when using automation during a 4-week field trial, Transportation Research F: Traffic Psychology & Behaviour, 82, 400-411, doi.org/10.1016/j.trf.2021.09.010.
Rehrl, K., and Gröchenig, S. (2021). Evaluating localization accuracy of automated driving systems. Sensors, 30, 21(17):5855. doi: 10.3390/s21175855.
Ren, J., and Xia, D. (2023). Challenges of autonomous driving systems. In: Autonomous driving algorithms and Its IC Design. Springer, Singapore.
Repairer Driven News. (2026, April 2). NTSB determines cause of 2 fatal BlueCruise-involved crashes, notes system safety limitations. https://www.repairerdrivennews.com/2026/04/02/ntsb-determines-cause-of-2-fatal-bluecruise-involved-crashes-notes-system-safety-limitations/

Reveille Racing and Dietz, E. (2023). A case study from the Indy Autonomous Challenge's simulation race. Journal of Technology, Management, and Applied Engineering, 39(1).
Rexer, M., Pelz, P. F., and Kuhr, M. M. G. (2025). Propagation of systematic sensor uncertainty into the frequency domain. ASME. ASME J. Risk Uncertainty Part B, 11(4): 041201. https://doi.org/10.1115/1.4067828
RoboRacer. (2025). The leading platform for autonomous racing education and research, https://roboracer.ai/
Roles, J. (2025). How self-driving technology is changing motorsport, Abu Dhabi Racing League Blog, Sept 22, 2025, https://a2rl.io/blog/18/How-Self-Driving-Technology-is-Changing-Motorsport
Russell, S. M., Blanco, M., Atwood, J., Schaudt, W., Fitchett, V. L., and Tidwell, S. (2018). Naturalistic study of Level 2 driving automation functions, Tech. Rep. DOT HS 812 642, National Highway Traffic Safety Administration, Washington, DC.
Sabery, S. M. (2026). Why investigating the impact of mud on automotive perception sensors is critical for ADAS and autonomous vehicles, Claytex, accessed on June 13, 2026, https://www.claytex.com/tech-blog/why-investigating-the-impact-of-mud-on-automotive-perception-sensors-is-critical-for-adas-and-autonomous-vehicles/
SAE International (2018). J3016_201806: Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (Warrendale: SAE International, 15 June 2018), https://www.sae.org/standards/content/j3016_201806/.
SAE (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles, Standard J3016_202104, Quality, Testing and Safety, Automated and Autonomous Systems. https://www.sae.org/standards/j3016_202104-taxonomy-definitions-terms-related-driving-automation-systems-road-motor-vehicles
Saeed, T.U., Alabi, B.N.T., Labi, S. (2021). Preparing road infrastructure to accommodate connected and automated vehicles: System-level perspective, Journal of Infrastructure Systems 27(1), 06020003
Saka, Z., and Labi, S. (2023). Investigation of AV operational issues using simulation equipment, CCAT Report #34, The Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.
Schlager, B., Goelles, T., Behmer, M., Muckenhuber, S., Payer, J., and Watzenig, D. (2022). Automotive lidar and vibration: Resonance, inertial measurement unit, and effects on the point cloud, in IEEE Open Journal of Intelligent Transportation Systems, 3, 426-434, 2022, doi: 10.1109/OJITS.2022.3176471
Seilabi, S. E., Pourgholamali, M., Miralinaghi, M., and Labi, S. (2026). Optimizing dedicated lanes and tolling schemes for connected and autonomous vehicles to address bottleneck congestion considering morning commuter departure choices, Journal of Intelligent Transportation Systems 30 (1), 37-54.
Seilabi, S.E., Tabesh, M.T., Davatgari, A., Miralinaghi, M., and Labi, S. (2022). Lane management in the era of CAV deployment, CCAT Report #72, The Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN.
Shalev-Shwartz, S., Shammah, S., and Shashua, A. (2017). On a formal model of safe and scalable self-driving cars. arXiv. https://arxiv.org/abs/1708.06374
Soltanirad, M., Baghersad, M. (2025). Perception technologies for autonomous transportation: A comparative analysis of LiDAR, radar, camera, and sonar, Computational Research Progress in Applied Science & Engineering, CRPASE: Transactions of Civil and Environmental Engineering 11, 1–10, Article ID: 2967, doi.org/10.82042/crpase.11.4.2967
Stewart, J. (2017). Meet the self-driving car built for human-free racing, Transportation, Wired, wired.com/2017/02/meet-self-driving-car-built-human-free-racing/
Stone, T., Santoni de Sio, F., and Vermaas, P.E. (2020). Driving in the dark: Designing autonomous vehicles for reducing light pollution. Sci. Eng. Ethics 26, 387–403.

Sun, H., Liu, X., Xu, K., Miao, J., and Luo, Q. (2021). Emergency vehicles audio detection and localization in autonomous driving. https://arxiv.org/abs/2109.14797
Suryana, L.E., Nordhoff, S., Calvert, S., Zgonnikov, A., van Arem, B. (2025). Meaningful human control of partially automated driving systems: Insights from interviews with Tesla users, Transportation Research Part F: Traffic Psychology and Behavior, 113, 213-236, https://doi.org/10.1016/j.trf.2025.04.026.
Sytner Group (2017). Introducing 'Roborace' - a Motorsport with Zero Humans. www.sytner.co.uk. Accessed 2026-9-16. https://www.sytner.co.uk/news/roborace
Tan, X., and Zhang, Y. (2024). A computational cognitive model of driver response time for scheduled freeway exiting takeovers in conditionally automated vehicles. Hum Factors, 66(5): 1583-1599. doi: 10.1177/00187208221143028.
TUV SUD (2026). Compliance with new automated lane keeping system regulation - TÜV SÜD, https://www.tuvsud.com/en/industries/automotive/autonomous-vehicle-testing-and-homologation-services/automated-lane-keeping-system, accessed on June 13, 2026.
UL (2023). UL 4600 Standard for evaluation of autonomous products, https://www.shopulstandards.com/ProductDetail.aspx?productid=UL4600
Ullrich, L., Buchholz, M., Dietmayer, K., and Graichen, K. (2026). Toward fully autonomous driving: AI, challenges, opportunities, and needs, IEEE Access 14, 17971-17997.
United Nations (2021). Uniform provisions concerning the approval of vehicles with regard to Automated Lane Keeping Systems Addendum 156 – UN Regulation No. 157, ECE/TRANS/WP.29/2020/81, United Nation, New York, NY. https://unece.org/sites/default/files/2023-12/R157e.pdf
UNECE (2021). UN Regulation No. 157 - Automated lane keeping systems (ALKS), E/ECE/TRANS/505/Rev.3/Add.156, https://unece.org/transport/documents/2021/03/standards/un-regulation-no-157-automated-lane-keeping-systems-alks
UNECE (2022). UN Regulation extends automated driving up to 130 km/h in certain conditions, https://unece.org/sustainable-development/press/un-regulation-extends-automated-driving-130-kmh-certain-conditions
US Department of Transportation (2020). How connected vehicles work, US Department of Transportation, Washington, DC. https://www.transportation.gov/research-and-technology/how-connected-vehicles-work
Vargas, J., Alsweiss, S., Toker, O., Razdan, R., and Santos, J. (2021). An overview of autonomous vehicles sensors and their vulnerability to weather conditions. Sensors, 21(16), 5397. https://doi.org/10.3390/s21165397
Vargas Rivero, J.R., Gerbich, T., Teiluf, V., Buschardt, B., and Chen, J. (2020). Weather classification using automotive LIDAR sensor based on detections on asphalt & atmosphere. Sensors, 20, 4306.
Vehicle Integration Team at Waymo (2023). Guided by the flow: The role of aerodynamics in shaping the Waymo Driver, accessed on June 13, 2026, https://waymo.com/blog/2023/05/guided-by-flow-role-of-aerodynamics/
Velocity (2023). Vibration, the not so silent killer of INS, and ways to mitigate its effects, Hexagon and Novatel, https://novatel.com/tech-talk/velocity-magazine/velocity-2023/vibration-the-not
Viktor, P, and Kiss, G. (2026). Sensors in self-driving vehicles: A detailed literature review and new Trends. Sensors (Basel). 26(7), 2153. doi: 10.3390/s26072153.
Wall Street Journal (2026). The most polite trucker in America is a driverless 18-wheeler, article by Esther Fung, https://www.wsj.com/business/driverless-trucks-18-wheeler-aurora-35b89c45
Wang, D., Ghoreishi, S.F. (2026). Probabilistic adaptation for robust decision-making of autonomous vehicles in non-stationary environments. Int. J. ITS Res. https://doi.org/10.1007/s13177-026-00685-y
Wang, M., Parker, J. I., Wong, N., Mehrotra, S., Roberts, S. C., Kim, W., Romo, A., and Horrey, W. J.

(2023). Human-machine interfaces and vehicle automation: The effect of HMI design on driver performance and behavior, Emerging Technologies Technical Report, AAA Foundation for Traffic Safety. https://rosap.ntl.bts.gov/view/dot/72287

Wang, S., Fong, R., Yuan, G., and Yuan, F. (2021). Vibration-based damage imaging via high-speed cameras with 3D digital image correlation using wavelet transform, SPIE Conference Proceedings, DOI:10.1117/12.2585246

Wang, Y., Alhuraish, A., Wang, S., and Zhou, H. (2025). Empirical performance evaluation of lane keeping assist on modern production vehicles, Pre-prints, https://arxiv.org/abs/2505.11534

Wischnewski, A., Geisslinger, M., Betz, J., Betz, T., Fent, F., Heilmeier, A., Hermansdorfer, L., Herrmann, T., Huch, S., Karle, P., Nobis, F., Ögretmen, L., Rowold, M., Sauerbeck, F., Stahl, T., Trauth, R., Lienkamp, M., and Lohmann, B. (2022). In: Pfeffer, P. (Ed.) 12th International Munich Chassis Symposium 2021. Proceedings. Springer Vieweg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-64550-5_10
Proceedings, 163-182. https://doi.org/10.1007/978-3-662-64550.

Wischnewski, A., Stahl, T., Betz, J., and Lohmann, B. (2019). Vehicle dynamics state estimation and localization for high performance race cars. IFAC-PapersOnLine 2019, 52, 154–161.

Wu, Y. (2025). Comparative Analysis of LiDAR, radar, and camera sensors for autonomous perception: Principles, challenges, and fusion strategies, Applied and Computational Engineering, 190,74-80. doi.org/10.54254/2755-2721/2026.TJ28614

Wu, Z., Song, Y., Liu, J., Chen, Y., Sha, H., Shi, M., Zhang, H., Qin, L., Liang, L., Jia, P., Qiu, C., Lei, Y., Wang, Y., Ning, Y., Zhang, J., and Wang, L. (2024). Advancements in key parameters of frequency-modulated continuous-wave light detection and ranging: A research review. Applied Sciences, 14(17), 7810. https://doi.org/10.3390/app14177810

Wu, Z., Pan, B., Wang, J., Li, M., Jiang, W., Liu, Z., Zhang, C. (2026). Sensor calibration for autonomous driving: A survey, Measurement, 287, 122492, doi.org/10.1016/j.measurement.2026.122492.

Xu, M., Liu, Z., Wang, B., and Li, S. (2025). A survey of autonomous driving trajectory prediction: Methodologies, challenges, and future prospects. Machines, 13(9), 818. https://doi.org/10.3390/machines13090818

Yahiaoui, L., Uricar, M., Das, A., and Yogamani, S. (2020). Let the sunshine in: Sun glare detection on automotive surround-view cameras, in Proc. IS&T International Symposium on Electronic Imaging: Autonomous Vehicles & Machines, 80-1 to 80-9, https://doi.org/10.2352/ISSN.2470-1173.2020.16.AVM-080

Yan, S., Liu, X., and Zhao, J. (2024). Automatic miscalibration detection and correction of LiDAR and camera using motion cues. Chinese Journal of Mechanical Engineering, 37. https://doi.org/10.1186/s10033-024-01035-3

Yang, B., Inoue, K., Kitazaki, S., and Nakano, K. (2021). Influences on drivers' understandings of systems by presenting image recognition results. In 2021 IEEE Intelligent Vehicles Symposium Workshops (IV Workshops), 19-24.

Yang, L., Zhang, X., Li, J., Wang, C., Song, Z., Zhao, T., Song, Z., Wang, L., Zhou, M., and Shen, Y. (2024). V2X-Radar: A multi-modal dataset with 4D radar for cooperative perception. arXiv. https://arxiv.org/abs/2411.10962

Yang, Y., Zhu, D., Qu, T., Wang, Q., Ren, F., and Cheng, (C. 2022). Single-stream CNN with learnable architecture for multisource remote sensing data, in IEEE Transactions on Geoscience and Remote Sensing, 60, 1-18, 5409218, doi: 10.1109/TGRS.2022.3169163.

Yao, S., Guan, R., Peng, Z., Xu, C., Shi, Y., Yue, Y., Lim, E.G., Seo, H., Man, K.L., Zhu, X., and Yue, Y. (2023). Radar perception in autonomous driving: Exploring different data representations, https://arxiv.org/html/2312.04861v1

Ye, X., and Wang, X. (2022). Operational design domain of automated vehicles at freeway entrance terminals, Accident Analysis & Prevention, 174, 106776, doi.org/10.1016/j.aap.2022.106776.

Yu, G., Li, H., Wang, Y., Chen, P., and Zhou, B. (2022). A review on cooperative perception and control supported infrastructure-vehicle system, Green Energy & Intel. Trans. 1(3), 100023.
Zhang, B., de Winter, J., Varotto, S., Happee, R., and Martens, M. (2019). Determinants of take-over time from automated driving: A meta-analysis of 129 studies. Transportation Research. Part F: Traffic Psychology and Behavior, 64, 285-307. https://doi.org/10.1016/j.trf.2019.04.020
Zhang, W., Zhang, H., Ding, H., Ding, H., Di, Y., Liu, J. (2025). CAV-dedicated lane sharing strategy of expressway in mixed traffic environment: A novel dynamic lane-level tolling method, Transportation Research Part A: Policy and Practice, 199, 104567, doi.org/10.1016/j.tra.2025.104567.
Zhang, Y., Carballo, A., Yang, H., and Takeda, K. (2023). Perception and sensing for autonomous vehicles under adverse weather conditions: A survey. ISPRS Journal of Photogrammetry and Remote Sensing, 196, 146-177. https://arxiv.org/abs/2112.08936
Zhang, Z., Morley Mao, Z., and Feng, Y. (2026). Hardening the CAV ecosystem to reduce cybersecurity risks – Year one, CCAT, University of Michigan, Ann Arbor, MI.
Zhao, J., Su, S., Liu, X., Wang, J., Tang, D., and Wang, Y. (2025). Numerical and experimental investigations of the aerodynamic drag characteristics and reduction of an autonomous vehicle, Physics of Fluids, 37(1), 015152.
Zhao, Q., Xiong, W., Liu, J., Huang, T., and Zhu, B. (2026). 4D-CAAL: 4D radar-camera calibration and auto-labeling for autonomous driving. arXiv. https://arxiv.org/abs/2601.21454
Zhao, J., Su, S., Liu, X., Wang, J., Hu, S., and Wang, Y. (2026). Multi-objective aerodynamic optimization of sensor shapes for autonomous vehicles under crosswind conditions, Physics of Fluids, 38(3), DOI:10.1063/5.0317150

APPENDIX 1.
Publication Abstract

Publication 1.

Ha, Y.J., Filipovska, M., Chen, S., & Labi, S. (2025). Autonomous vehicle fleet operations with constrained entropy-based dynamic autonomous vehicle routing: Insights for environmentally conscious shared mobility. *Multimodal Transportation*, 5(1), 100236 https://doi.org/10.1016/j.multra.2025.100236

With growing concerns over urban congestion and its associated economic, environmental, and societal costs, innovative solutions are urgently needed. Autonomous vehicles (AVs) offer a promising opportunity to improve urban transportation efficiency, safety, and sustainability. This study introduces a novel framework, DRL-CEDAR, which combines deep reinforcement learning (DRL) for optimizing AV acceleration and a dynamic routing algorithm, Constrained Entropy-based Dynamic AV Routing (CEDAR), to strategically guide AVs through urban traffic networks. The DRL module trains AVs to reduce emissions and fuel consumption while increasing vehicle speeds, while the CEDAR module enables AVs to interact with human-driven vehicles (HDVs) to mitigate network-wide congestion. Simulation results on a midtown Manhattan network demonstrate that even with a 10% AV adoption rate, DRL-CEDAR achieves reductions of 34% in CO emissions, 11% in CO2 emissions, and 78% in vehicle waiting times compared to conventional routing methods. These findings underscore the potential of DRL-CEDAR to significantly improve urban traffic conditions and support sustainable mobility goals.

APPENDIX 2.
New Courses at Purdue University Motivated by this CCAT Project

2.1. ARES: Autonomous Race-Engineering Systems (VIP Course)

Introduction: The ARES (Autonomous Race-Engineering Systems) course explores robotics, perception, controls, AI-ML methods, and adversarial racing strategies to develop solutions to address a variety of multi-disciplinary problems in high-speed autonomous Racing (AR) with real world applications across multiple modes and platforms.

Course Advisor: Samuel Labi

Course Instructors and Mentors: Andres Moreno, Joseph Reed, Richard Ajagu

Course Description: This VIP course serves as a testbed for advancing research and innovation in self driving technology through the study of Autonomous Racing Systems and its real-world applications. The course explores latest advancements in robotics, AI-ML methods, Race Theory and Engineering skills.

Website: For more information on the course, visit the website:
https://engineering.purdue.edu/VIP/teams?q=ares

Areas of interest: (a) controls, localization, path planning and navigation in high-speed AR environments, adversarial decision making, and safety-critical edge cases, and/or
(b) other aspects/applications of AR beyond the track, to include perspectives of road infrastructure design, human factors, economics, and other real-world contexts of AR systems.
Different Topics that can be explored on this course: Cyber-Physical AI, Deep Learning, Control Systems, High-speed autonomy, Multi-agent Adversarial Strategy and Decision-making, Overtaking, Sensor Fusion, ROS, Platform Optimization, Simulation (Digital Twin), Reinforcement Learning, Software Development, System Integration, Real-world Applications & Systems Analysis, Infrastructure Design, and the Economics and Business applications of AR Systems.

Eligibility: All levels (freshmen, sophomores, juniors and seniors) in any department.

Application Platforms: Full size racecars, Go-karts, Small-size road/track race cars, F1-Tenth, Boats, Submarine, Drones and Rally/Offroad.

2.2. Autonomous Motorsports Purdue (AMP) (VIP Course)

Introduction: Bridging motorsports and autonomy, AMP VIP works together with the AMP Student Club to build and autonomize go-kart platforms for autonomous go-kart racing. One of the main competitions AMP participates in is the Autonomous Karting Series (AKS), an inter-college go-kart race that takes place at the Purdue Gran Prix track, where teams test their autonomous kart and compete, pushing the limits of their creation at the track. The building, development and implementation of such platforms involve the deployment of challenging hardware, software and mechatronics problems that students can choose to work on with highly applicable skills sought after by industry.

Course Advisor: Samuel Labi

Course Instructors and Mentors: Andres Moreno, Joseph Reed, Richard Ajagu

Description: AMP VIP works together with the AMP Student Club to build and autonomize go-kart platforms for autonomous go-kart racing. This VIP gives students the opportunity to pursue research of their interest related to autonomous kart racing, where high-speeds, precision, accuracy, robustness and safety are imperative.

Websites: For more information on the course, visit the website:
https://engineering.purdue.edu/VIP/teams?q=amp
For more information on the competition, visit the website:
https://www.autonomouskartingseries.com/

Areas of Interest: Design, construction, optimization and "autonomization" of go-kart platforms; Digital Twin and Simulation of autonomous go-karts; Cyber-physical AI; Software development for path planning, perception, controls, localization, sensor fusion, ML, AI, RL; Racing strategies. (Raceline optimization, overtaking strategies, braking and throttling strategies); Business applications in AMP (sponsorship, business strategy, marketing, publicity)

Pre-requisites: The following skill is required to enter this VIP: Willingness to learn.
The following skills are NOT a requirement for entering, but will be aligned with this VIP: Mechanical, electrical, electromechanical, and/or mechatronics design; Software development (Robot Operating System (ROS), Matlab, Simulink, Python, C++, AI, ML); Ability to create, improve and properly use simulation tools; Building circuits, mechanical assemblies, CAD; Good teamwork and communication; Experience in robotics, autonomous vehicles.

2.3. ROBOAT: Autonomous AI Maritime Maneuvers (AIMM)

Introduction: The project (also referred to as RoBoat) involves hands on problems, development of the sensor suite for the boat, algorithms capable of autonomizing the boat, including perception, path planning, controls, localization, integration and simulation.

Course Advisors: Brittany Newell and Samuel Labi

Course Instructors and Mentors: Andres Moreno, Joseph Reed, Richard Ajagu

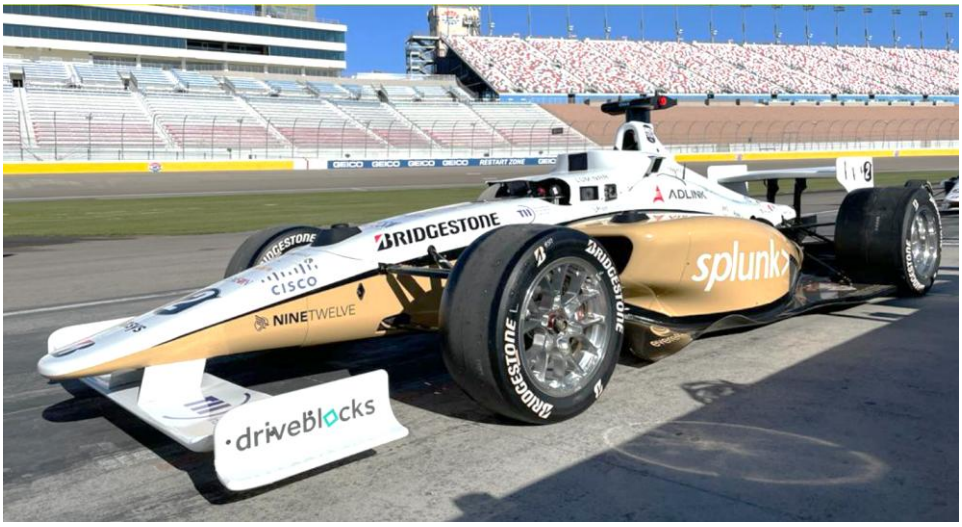
Description: RoBoat participates in the AIMM ICC competition, where students install sensors on a boat and develop the software to pass the series of challenges. This project involves hands on problems, development of the sensor suite for the boat, algorithms capable of autonomizing the boat, including perception, path planning, controls, localization, integration and simulation. This experience provides in-depth learning in important fields like machine learning, artificial intelligence, circuits, mechatronics, and naval engineering, under the fun and excitement of a competition. Offering opportunities for students to delve into hot research topics highly applicable in modern-day technical area related industry.

Websites:
For more information on the course, visit the website:
https://engineering.purdue.edu/VIP/teams?q=roboat

For more information on the competition, visit the website:
https://www.trine.edu/innovation-one/aimm/index.aspx

Areas of Interest: Naval engineering; autonomous driving and robotics; design and building of an autonomous boat; sensor suite, at hardware level and software level; physical AI; software development: robot operating system, ML, deep learning, path planning, localization, controls, system dynamics, perception; artificial intelligence; machine learning; maritime maneuvering.

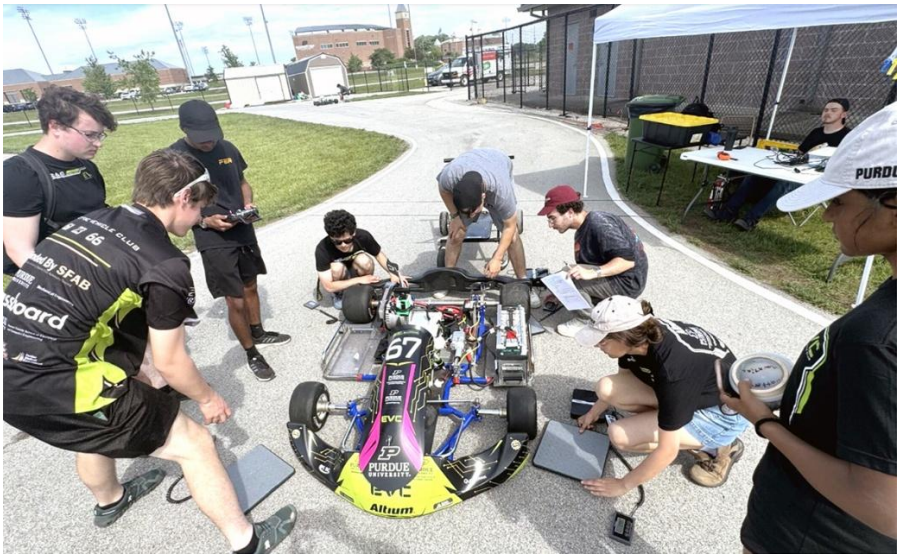
APPENDIX 3
Autonomous Racing Competitions where Purdue University Teams were Partially Supported by this CCAT Project



Vehicle of the Purdue University team (Black and Gold, now called Purdue AI Racing) at the **Indy Autonomous Challenge (IAC)** event in Las Vegas, NV, in 2023. University teams from around the world competed with their full-size fully autonomous vehicles.



The Purdue University team (Roboat) and their vessel at the **Artificial Intelligence Maritime Maneuver Indiana Collegiate Challenge (AIMM ICC)** sponsored by the US Navy, in Angola, IN, in 2025. Students from universities in Indiana competed in various maneuvers related to core mission sets (supply delivery, stealth runs, target location, interception, and rescue).



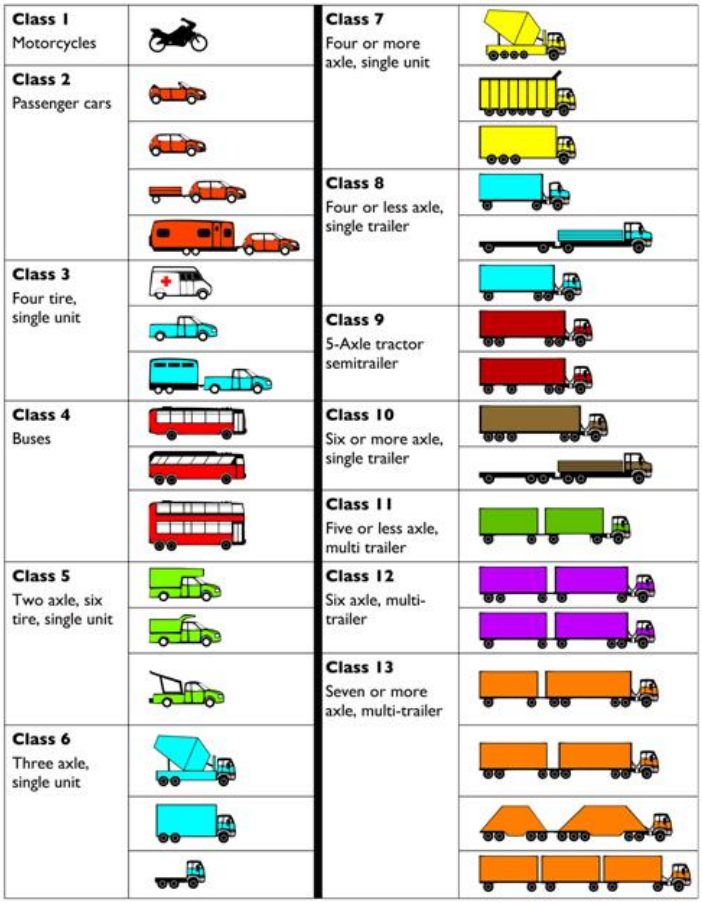
One of the Purdue University teams at the **Autonomous Karting Series** event in West Lafayette in 2026, where university student clubs from the USA and Canada raced their autonomous go-karts, pushing the limits of robotics and self-driving technology.



The Purdue University team (Boiler Autonomy) at the 31st **RoboRacer Autonomous Racing Competition** in Detroit in 2026, where students operated their 1:10 scale open-source fully autonomous race cars, competing at the IEEE Intelligent Vehicles Symposium (IEEE IV 2026), Detroit, MI.

APPENDIX 4
FHWA Vehicle Classes

The Federal Highway Administration (FHWA) uses a standard 13-category vehicle classification system based on axle count, tire configuration, and trailer presence.



Source of Image: FHWA Traffic Monitoring Guide, Vehicle Types Figure C-1 FHWA 13 vehicle category classification https://www.fhwa.dot.gov/policyinformation/tmguide/tmg_2013/vehicle-types.cfm.