CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Final Report #53
September 2023

Development of Situational Awareness Enhancing System for AV-to-Manual Handover and Other Tasks

Yujie Li
Aishwarya Sharma
Bortiorkor N.T. Alabi
Sikai Chen
Samuel Labi

PURDUE UNIVERSITY

CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Report No. 53
Project Start Date: January 2021
Project End Date: August 2022

September 2023

Development of Situational Awareness Enhancing System for Manual Takeover of AV

by

Yujie Li
Graduate Researcher

Aishwarya Sharma
Graduate Researcher

Ajuna P. John
Graduate Researcher

Bortiorkor Alabi
Graduate Researcher

Sikai Chen
Visiting Asst. Professor

Samuel Labi
Professor

Purdue University

ACKNOWLEDGMENTS AND DISCLAIMER

Funding for this research was provided by the Center for Connected and Automated Transportation under Grant No. 69A3551747105 of the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R), University Transportation Centers Program. Also, general support was provided by the Center for Innovation in Control, Optimization, and Networks (ICON) and the Autonomous and Connected Systems (ACS) initiatives at Purdue University's College of Engineering. The companies, institutions and professors that provided valuable in-kind cost share or other external support for this project, including ETH Zurich (Dr. Bryan Adey), Nanyang Technical University (Dr. Feng Zhu), and TU Delft (Dr. Goncalo Homem de Almeida Correia), and other institutions are also acknowledged. Other general support was provided by Deepak Benny, Sayali Pawar, Jelin Sabu, and Purdue's Black & Gold's Autonomous Racing Team (Alec Pannunzio, Andres Moreno, Frank Dong, Haoguang Yang, Manuel Mar, Richard Ajagu, Shashank Modali, Shreya Ghosh, and Zainab Saka). The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Cover Photo Credit: Chethan KVS, unsplash.com/photos

Suggested APA Format Citation:
Li, Y., Sharma, A., John, A.P., Alabi, B.N.T., Chen, S., 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.

Contacts

For more information

Samuel Labi, Ph.D.
Purdue University
550 Stadium Mall Drive
HAMP G167B
Phone: (765) 494-5926
Email: labi@purdue.edu

CCAT
University of Michigan Transportation
Research Institute
2901 Baxter Road
Ann Arbor, MI 48152

uumtri-ccat@umich.edu
(734) 763-2498
www.ccat.umtri.umich.edu

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
53		

4. Title and Subtitle: Development of situational awareness enhancing system for manual takeover of AV	**5. Report Date** September 2023 **6. Performing Organization Code** N/A
7. Author(s) Yujie Li, Aishwarya Sharma, Ajuna P. John, Bortiorkor N.T. Alabi, Sikai Chen, Samuel Labi	**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; and University of Michigan Ann Arbor, 2901 Baxter Road, Ann Arbor, MI 48109	10. Work Unit No. **11. Contract or Grant No.** Contract No. 69A3551747105
12. Sponsoring Agency Name and Address U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE, Washington, DC 20590	**13. Type of Report &Period Covered** Final report, Jan 2019 – Aug 2022 **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
Partial- and conditional-automated driving systems (ADS) can not only assist drivers with their driving tasks but also significantly reduce the driving-related burden. Yet still, when the AVS is engaged, the human driver still plays a critical role such as monitoring the driving environment and performing certain driving tasks when called upon by the ADS. There exists ample evidence in the literature on simulation experiments and real-world that point to the difficulty of human drivers to maintain the requisite situational awareness to safely take over the vehicle when needed. This is often due to the nature of the non-driving related tasks in which they typically engage, low vigilance, and excessive trust in ADS capabilities. There exists a need to assist drivers to maintain a certain minimal level of situational awareness, to promote smooth and safe transition of the vehicle from the automated driving system to manual control where necessary. This study developed inputs for an in-vehicle situational awareness enhancing system (SAES) and a prototype SAES, to facilitate AV-to-manual takeover in partially and conditionally automated vehicles. The study is predicated on the notion that appropriate inputs to SAES can help it effectively direct drivers' attention to prospective AV-to-manual transition thereby increasing takeover quality and reducing takeover time. This study also synthesized evidence from past studies on the benefits of enhanced situational awareness on takeover performance in partial- and conditional-automation driving environments. Finally, a SAES case study involving comfortable headways was carried out through a cab-driving simulation experiment. At a broader level, the study results can help guide the design of in-vehicle alerts intended to enhance situational awareness and the development of AV operator training manuals.

17. Key Words	18. Distribution Statement
Autonomous vehicles, Situational awareness, Takeover	No restrictions.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	74	

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

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

ACC	Adaptive Cruise Control
ADS	Automated Driving System
AOI	Areas of Interest
AV	Autonomous Vehicle
AVO	AV Operator
AVS	Automated Vehicle System
CAV	Connected and Autonomous Vehicle
HDV	Human-driven Vehicle
HMI	Human-machine Interface/Interaction
HVI	Human-vehicle Interface/Interaction
IOO	Independent Owner or Operator
NDRT	Non-driving Related Task
NHTSA	National Highway Traffic Safety Administration
SA	Situational Awareness
SAE	Society of Automotive Engineers
SAES	Situational Awareness Enhancement System
SAGAT	Situation Awareness Global Assessment Technique
SAPM	Situation Present Awareness Method
SART	Situation Awareness Rating Technique
TOD	Takeover Duration
TOP	Takeover Propensity
TOR	Takeover Request
TOT	Takeover Time (spent)
TOTB	Takeover Time Budget
TOW	Takeover Warrant
TTC	Time to Collision
TTFG	Time to First Glance
TTFH	Time to First Hands
TTT	The Twenty-question Task
V2X	Vehicle-to-Everything

CHAPTER 1. INTRODUCTION

1.1 Study Background

As society transitions into an era of transportation automation, issues related to human-machine interface are becoming increasingly paramount. It is universally acknowledged that the benefits of automation (including safety and mobility) and other impacts will be profoundly influenced by the extent of the vehicle's human operator awareness of their operating environment. Regarding automated transportation, one of the most discussed areas of human-machine interaction, is the takeover of the machine (that is, the AV) by the human operator. Key issues associated with human takeover of AVs include the measurement and characterization of risk, establishing risk thresholds for takeover, designing takeover alert mechanisms, understanding the human driver's propensity to take over, determining takeover duration, and assessing the effectiveness of the takeover. For these to happen, it is imperative that the AV driver maintains situational awareness of traffic roadway conditions.

1.2 Problem Statement and Study Objectives

During the period of transition to full vehicle automation, driving responsibility will be shared between the automated vehicle system (AVS) and the human driver. An SAE Level 2 (i.e., partial automation) vehicle can execute steering and acceleration/deceleration tasks but requires the human driver to continuously monitor the roadway and traffic environment and to perform the driving tasks when and where needed.

The literature contains evidence that supports the notion that the monotonous nature of monitoring tasks (such as that typically of a Level 2 automated vehicle) could lead to task underload and vigilance reduction (i.e., deterioration in the ability to remain vigilant) (Scerbo and Mouloua, 1999). In SAE Level 3 (i.e., conditional automation), the automated driving system carries out the driving task (this allows the human driver to be occupied with non-driving related tasks but requires them to take over vehicle control under certain circumstances. In Level 3 automated vehicles, when the driver takes his/her mind off the driving task significantly degrades his/her situational awareness (SA) which, in turn, reduces takeover performance and increases accident risk. It is important to recognize that situational awareness refers to awareness of the AV operator not the vehicle.

A high situational awareness could be rendered ineffective in certain cases, for example, where the driver has over-reliance and over trust in the AVS's capabilities, and thus is overly complacent. A prominent real-world example is when a car in self-driving mode crashed on a Florida highway in May 2016 (The Guardian, 2016). The driver may have been attentive but probably trusted the car to handle the situation.

Therefore, it is important to design mechanisms that promote, or even prompt the AV driver to maintain a certain minimum level of awareness of the prevailing roadway, traffic situation or conditions. Some automobile manufacturers have taken measures to actively ensure that the human AV operator has a minimum level of situational awareness. For example, Tesla's Autopilot and Nissan's ProPilot, both of which promise Level 2 automation, require drivers to have their hands on the steering wheel in certain situations and Cadillac's Super Cruise system introduced an in-vehicle camera to track drivers' head position and gaze to ensure the driver's attention on the road ahead (Hanley, 2019). Such mechanisms could involve a physical action by the driver and thereby reduce their overall reaction time to any subsequent safety event needing their attention. Conventional wisdom such as "eyes on the road" may not be sufficient for drivers when they are using Level 2 or Level 3 AVS. Nevertheless, such AVSs in the practice, are still unable to fully address the key underlying issue of enhancing the driver's situational awareness.

1.3 Study Objectives

The study develops inputs needed to build a situational awareness enhancement system (SAES) that has general roadway applications, but is intended for human-takeover of control from the AV:

- Evaluate takeover alert mechanisms.
- Discuss the propensity of the human operator to takeover, including the factors.
- Discuss the takeover duration and effectiveness, including the factors.
- Develop inputs towards a process to measure risks associated with takeover.
- Present a case study where situation awareness considerations provide insights into AV operations policy.

1.4 Study Approach

This study investigates the affecting factors that need to be considered in designing an in-vehicle situational awareness enhancing system (SAES), which can facilitate AV-manual takeover given partial and conditional automation. The research is divided into two phases. In the first phase, we present a thorough literature review that explores prompt-based SAES for directing drivers' attention to AV-manual takeover and evaluate their impacts on drivers' situational awareness and takeover performance, and we develop SAES inputs and a general SAES that could serve as a starting point for future SAES development. In the second phase, we present a driving simulator-based experiment that investigates factors including headways and traffic conditions. This study synthesizes evidence from past studies; on interactive driving simulator-based experiments with SAES. The collected information is used to describe the impacts of SAES on drivers' situational awareness and takeover performance in partial and conditional automation driving environments.

1.5 Organization of this Report

The report first presents AV concepts as the background for the study (Chapter 2) and how they relate to situational awareness and manual takeover. This consists of a discussion of AV technology readiness, the various levels of automation, features of automation and connectivity, the anticipated timeline of AV emergence/deployment on public roads, and the role of traffic safety. This background is provided to show how these various concepts and developments and their trends could influence the AV driver's situational awareness or are influenced by it. Next, the report discusses the concepts of situational awareness in the context of automated driving (Chapters 3 and 4). In Chapter 5, a SAES-related case study is presented to show how situational awareness helps to develop AV operations, through a driving simulator study. Chapter 6 of the report provides concluding remarks including the summary, study limitations, and directions for future research. Chapter 7 presents the USDOT performance indicators achieved, and Chapter 8 lists the study outcomes and outputs.

CHAPTER 2. AV CONCEPTS AND RELATION TO SITUATIONAL AWARENESS AND MANUAL TAKEOVER

In this chapter, the report presents a few concepts related to AV capabilities and operations. It is important to discuss these topics because AV features and capabilities will influence not only the situational awareness of AV drivers, but also the specific application context of manual takeover of the AV, (that is, the warrants, mechanisms, and effectiveness). This chapter discusses AV technology readiness, the various levels of automation, features of automation and connectivity, the anticipated timeline of AV emergence/deployment on public roads, and the role of traffic safety.

2.1 Readiness of AV Technology

At the time of report, researchers generally agree that significant time and effort (regarding testing and regulatory approval) are needed before AVs will be considered ready to operate reliably and safely in all traffic and roadway conditions (McLeod, 2021). Significant technological advances must happen before AVs will be capable of operating not only at normal conditions but particularly in environments made complicated by the presence of other road users (say, the vulnerable kind), unexpected road surface conditions (including potholes and roadway debris), heavy fog, disabled vehicles, and work zones. AVs, as of 2021, were considered to have reached a level of 6 on the 10-point *Technology Readiness Level* scale (McLeod 2021). Technology Readiness Level (TRL) is a pertinent issue in the concept of manual takeover of AV because TRL will influence (and also, will be influenced by) AV takeover warrants, duration, and performance (effectiveness).

2.2 Levels of Vehicle Automation and Relationship with Situational Awareness

Any discussion of manual-takeover of AV must necessarily include a review of the standard levels of autonomy (LOA) vehicle autonomy/automation as defined by SAE International (the erstwhile Society of Automotive Engineers) in 2014 (SAE, 2014), and revised in 2016 and by the NHTSA (2016). Similar to TRL (discussed in the preceding section), LOA is an important consideration in takeover discussions because LOA will influence (and also, will be influenced by) the takeover warrants, duration, and performance (effectiveness).

Figure 2.1 presents the classification of automated driving features, from Level 0 (no driving automation) to Level 5 (full automation). At Level 0, the human driver carries out all driving tasks and the vehicle does not handle any aspect of the driving task. The vehicle may include driver assistance features such as blind-spot and lane-departure warnings. At Level 1, the vehicle can control one aspect of the driving task: either the steering or the speed, for example, cruise control and lane centering. At Level 2, the vehicle has both lateral and longitudinal control (the ADS controls both the steering and speed) but always requires full driver attention. At Level 3 (conditional driving automation), the driver does not drive the vehicle while the automated system is engaged, under certain conditions; however, the driver must be ready at any time to takeover if the system becomes disengaged. At Level 4, there is no need for a driver, and no need for a steering wheel and pedals in the vehicle. Level 4 vehicles are ODD specific – they can operate only within a specific geofenced area, and the vehicle disengages and comes to a stop on its own if it encounters a problem. Level 5 is fully self-driving and does not require human involvement. Unlike Level 4, the vehicle is not ODD specific that is, it can operate autonomously in all locations and under all conditions.

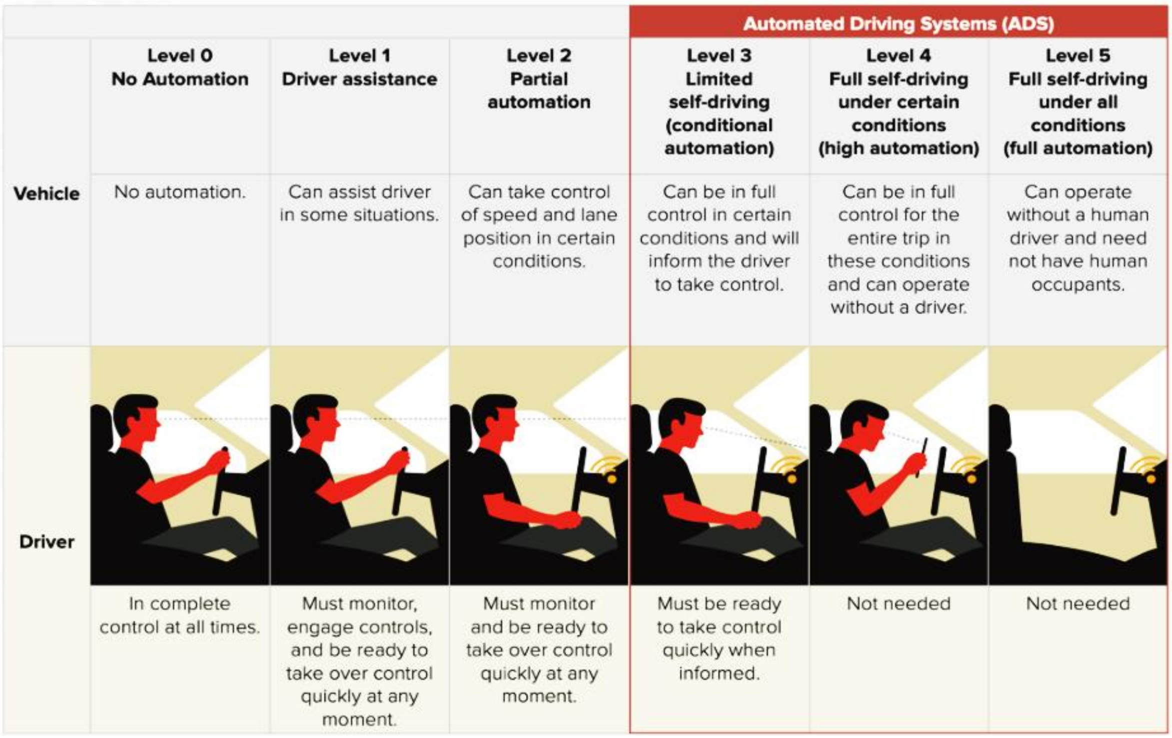


Figure 2.1 The SAE levels of automation (GHSA, 2018)

Subsequently, these guidelines were questioned by certain researchers for being vague, for example, the technology leap from Level 2 upward is not as linear as the guidelines suggest, and some vehicle manufacturers considered Level 2 to be too broad. As such, in 2021, SAE released updated descriptions of the levels of driving automation. The update added new terminologies and significantly refined concepts that had not been adequately understood by users of past versions, and restructured the definitions to incorporate additional classes that are more logical. These include additional clarity regarding the differences between Levels 3 and 4; new terms and definitions for remote driving and remote assistance; adopting the “Driver Support Systems” moniker for SAE Levels 1 and 2; definitions of vehicle types by groups, and classes of sustained driving automation; and clarifying and defining the concept of failure mitigation strategy (SAE 2021).

A discussion of the levels of automation is important because at least one of these levels requires the AV operator to take over the driving task in certain risky conditions. From a general perspective, the need to provide oversight to autonomous vehicles is expected to persist until they reach Level 5 where human takeover (and thus situational awareness) is obviated because the vehicle possesses the capability for fully autonomous driving operations under all types of road environment. NHTSA (2013). Until that happens, it has been stated that it is important for AV operators to possess adequate levels of situation awareness in various AV driving scenarios and roadway/traffic environments (Martelaro et al., 2015).

A critical prerequisite for human takeover from the AV is that the operator must have adequate situational awareness of the driving environment (roadway features and traffic conditions). As shown in Figure 2.1, for Levels 2-4, there is an anticipated occurrence of human takeover. In Level 2, the driver is the default controller and maintains control most of the time; in Level 4, the ADS is the default controller and is in control most of the time. The case for Level 3 lies in between that for Level 2 and level 4. Figure 2.2 presents a conceptual and hypothetical relationship between the situational awareness needed by the vehicle operator for the driving task vs. the level of autonomy of the vehicle in question.

The relationship in the figure is only hypothetical and could be verified, refuted, or modified through a theoretical analysis, empirical study, or questionnaire survey. It serves as an initial basis for a discussion on such a relationship. At Levels 0 and 5 where there is no possibility of takeover, it can be argued that there is no need for takeover-related situational awareness. At Levels 1 (driver assistance) and 2 (partial automation), the driver will need to monitor, engage controls, and be ready to take over the vehicle control quickly at any moment, so situational awareness is vital at Level 1 and even more vital at Level 2 automation. At Level 4 (fully self-driving under some conditions), the vehicle can be in full control for the entire trip; however, the vehicle possesses driver-control features (steering, pedals, and accelerator), thus the driver's need for situational awareness is rather low.

At Level 3 (conditional automation with limited self-driving), the autonomous driving system can control the vehicle fully in certain conditions and alerts the driver to take over in risky or uncertain conditions. As such, the driver needs to have maximum situational awareness so they can be ready to take over quickly when they receive the alert. It is worth mentioning that researchers at Stanford University have developed a system, *Daze*, which assesses in-vehicle situation awareness during manual or automated driving in a real-time (Martelaro et al., 2015).

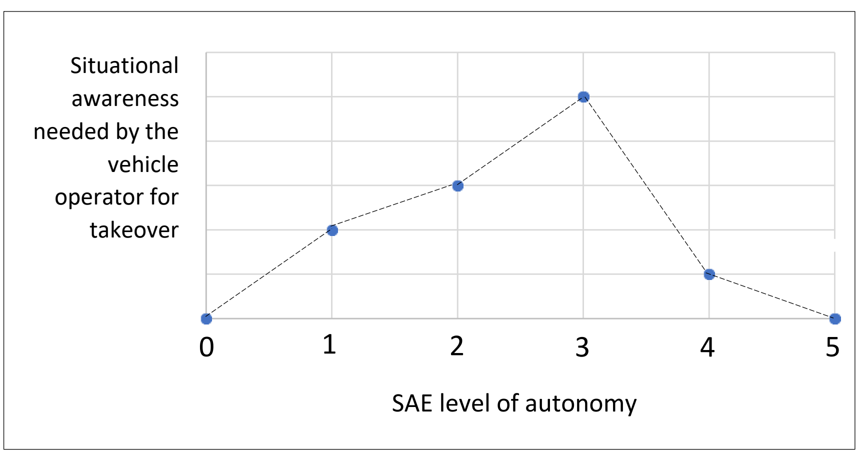


Figure 2.2 Level of situational awareness needed for the driving task vs. level of automation: Conceptual and hypothetical relationship.

2.3 Features of Automation and Connectivity that are related to Situational Awareness

AVs use sensor-based technology (cameras, lidar, and radar) and AI-based algorithms for image detection to characterize, in real-time, a 3-D representation of the vehicle's physical roadway and traffic environment (Figure 2.3). The cameras capture visual information, while lidar sensors use laser beams to measure distances and create detailed 3-D maps of the surroundings. Radar sensors detect objects and measure their speed and direction using radio waves.

These sensors work together to provide a comprehensive view of the vehicle's surroundings in real-time. Artificial intelligence algorithms then analyze the sensor data to identify objects, track their movements, and make informed decisions for safe navigation. The combination of cameras, lidar, and radar sensors enables the AV to accurately detect obstacles, recognize traffic signs and signals, and respond to complex driving scenarios. Such technologies ensure a high level of perception and decision-making capabilities and are key to AVs' efficient and reliable operations.

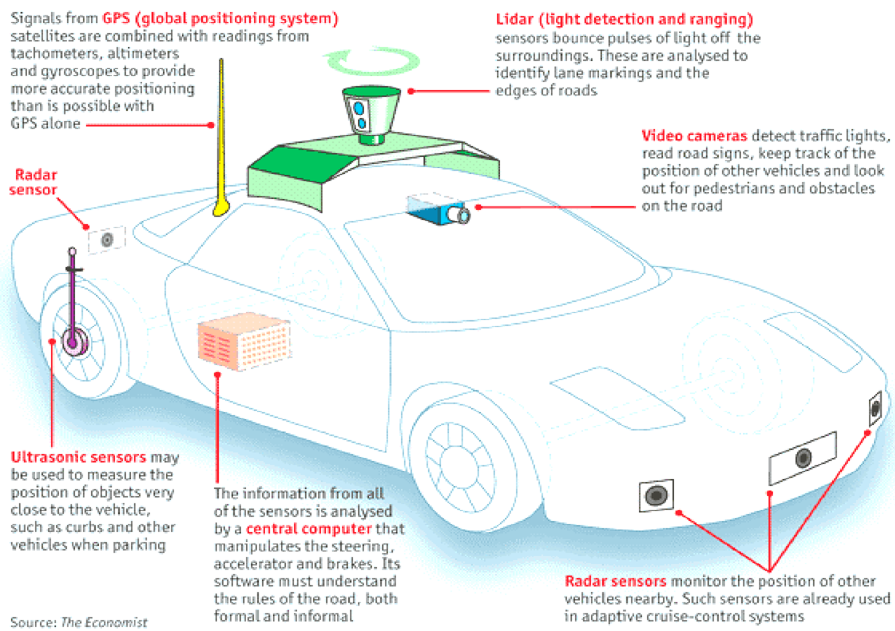


Figure 2.3 Basic sensing hardware of a typical autonomous vehicle
(Image source: Madhav (2019). circuitdigest.com/article/debunking-the-magic-behind-sensors-used-in-self-driving-cars)

Effective vehicle-to-infrastructure (V2I) connectivity can promote reliable AV operations. The zenith concept of connectivity, Vehicle-to-everything (V2X), refers to a communication ecosystem that enables and facilitates information exchange between the AV and all other types of entities in the ecosystem: vehicles (V2V), the grid (V2G), infrastructure including traffic signals (V2I), devices (V2D), and pedestrians (V2P). Ha et al. (2020) pointed out that automation and connectivity are sibling technologies. Other researchers have reported that potential applications of V2X connectivity have been identified by various national and international organizations including SAE International and the European Telecommunications Standards Institute (Kenney, 2011; ETSI, 2011; Harding et al., 2014; SAE, 2016). Yoshida (2013) have argued that AV technologies can realize their full potential only when the connectivity technology is fully developed. A few other researchers provided information that are suggestive of the critical role of V2X connectivity in promoting AV operations in a variety of safety-related traffic functions including traffic-related warnings (regarding, for example, blind spot, forward collision, approaching road work approaching emergency vehicle) and assists (for merging, intersection navigation, congestion prediction, and so on). Such capabilities are helpful in promoting the situational awareness of an AV driver.

2.4 The AV Transition Period and its Phases

It seems reasonable to suggest that fully autonomous operations will occur not spontaneously but in an evolutional and incremental manner over some extended period that is often referred to as the Transition Period (Figure 2.4). Several predictions have been made regarding the start year of AV deployment at public roads, the market penetration trends, level of autonomy trends, and the effects of experimental or initial AV deployment into the traffic stream. The incremental nature of the transition process is expected to be manifest regarding technology advancement, road user adoption, and infrastructure retrofit. During the transition period, it is expected that the roadways will accommodate a variety of vehicle types including Level 0 autonomy (traditional vehicle or vehicles operated fully by human drivers), Level 1 to Level 4 autonomy, and Level 5 autonomy, until a time in the far future when all vehicles on the road (100% market penetration) are fully autonomous.

The period of the transition could be described as consisting of four phases:

- Phase I, low AV-HDV ratio: up to 25% of vehicles on roadways are L4-5 AVs.
- Phase II, low-to-medium AV-HDV ratio: 25-50% of vehicles on roadways are L4-5 AVs.
- Phase III, mid-to-high AV-HDV ratio: 50%-75% of vehicles on roadways are L4-5 AVs.
- Phase IV, high HDV-AV ratio: 50%-75% of vehicles on roadways are L4-5 AVs.
- Fully autonomous phase (FAP): 100% of vehicles on roadways are L4-5 AVs.

Within these phases, there could exist sub-phases depending on the share of each level of autonomy. At the early years of the transition phase, the market penetrations of Levels 4-5 AVs will be low (as they are being tested for commercial use) and Levels 1-2 will be dominant in the traffic stream. With time, the market penetration of AVs will increase gradually to a point where AVs will dominate the traffic stream. This will be similar to the period in the early twentieth century when motor cars became dominant (and horse carriages became obsolete) and the latter were no longer considered in the design of road infrastructure.

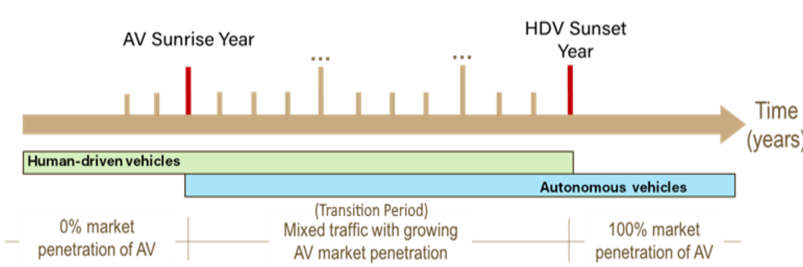


Figure 2.4 Timeline of HDV-only traffic, mixed traffic (transition period), and AV-only traffic

There exist several hypotheses and predictions regarding the initiation and length of the HDV-to-AV transition period. An IHS Automotive (2014) study expects the entire global fleet to be fully autonomous by 2050. It has been suggested that human driving will be restricted after 2060 if AV benefits are realized by that year (Litman, 2014). Also, it has been reported that the CEO of Tesla, an automotive industry giant, has suggested prohibiting the use of traditional (HDVs) subsequent to widespread adoption of AVs and their safety benefits is (Saeed, 2019). It may very well be the case that as AV demand grows, governments might be compelled to make policies prohibiting HDVs from certain corridors or classes of highways. It may take several decades for the HDV-to-AV transition.

The length of the transition period can be reduced by legislation (for example, banning HDVs from using certain corridors), AV technological advancements, enhanced protocols for HDV driver training towards the AV era, infrastructure investments to support AV operations, and improvements in public perceptions of AV safety. Kyriakidis et al. (2015) surveyed 5,000 individuals from over 100 countries and determined that approximately 70% of the respondents expect by the year 2050, NHTSA-defined Level 4 vehicles will achieve 50% market penetration. A recent study in Indiana (Saeed et al., 2018) suggested that 68% of individuals in small and medium-size cities prefer continuing using HDVs over AVs in all classes of ownership (shared use, hired, or self-owned).

The uncertainty in the expected length of the transition phase is governed by several factors, some of which are strongly related to human factors (lack of trust in automation), and are discussed in Pourgholamali et al. (2022) as follows:

- **Road user/driver attitudes**: It seems obvious that there will be marked variability across market segments (demographic groups, personal vs. commercial interests, etc.) in their willingness to give up their HDVs as soon as AVs become available.
- **AV policy**: some jurisdictions will be slow to provide supporting policies for AV operations and some may even pass policies to inhibit AV operations, both due to lack of trust in automation. For example, a few years ago, Krok (2016) reported that Chicago's City Council members, citing safety risk particularly to pedestrians, considered an ordinance that would prohibit autonomous car operations within city limits.
- **Inadequate infrastructure to accommodate AVs**: in some cases, the Independent Owner, or Operators (IOOs) might be unable to provide the infrastructure funding needed to support AVs due to already strained budgets. It will be important for public-sector IOOs to cultivate the skill of communicating with legislatures, to open the purse strings to support the building of renewed or new types of infrastructure, to support AVs.
- **Test outcomes**: Favorability of outcomes of experimental AV deployments at public roads and the press and media coverage in the event of any mishaps. AV successes seem to receive far less press reporting compared to AV mishaps. As more AV gets deployed gradually, the number of crashes (not crash rates) are also expected to increase. Every adverse AV incident will receive extensive coverage, thereby exacerbating the fears of an already skeptical public, increasing the reluctance of potential customers to patronize AVs, and leaving policymakers even more cautious to pass AV-supporting legislation and policies. In addition, any crash involving an HDV and AV will likely be blamed on the AV as it is the newcomer to the traffic stream, and the public mood might be governed by the maxim "it was not as bad until you came along."

It is expected that the above-discussed factors will influence the AV transition phase. As the safety and mobility benefits of AV become obvious, skepticism towards AVs will reduce and may lead to reduced length of the transition phase. Notwithstanding the effects of these factors, it seems to be generally agreed that the transition to a steady-state era of full autonomy will be gradual and evolutionary and will be punctuated with bumps and hiccups in AV purchase, patronage, or travel demand. It is also expected that there will be a bump (Figure 2.5) regarding the safety impacts of AVs (Labi, 2023): in the early years of the transition period, heterogeneity associated with mixed traffic will cause increased crashes, mostly caused by errant HDVs (because AVs will be tuned to drive conservatively to gain public support). The increased crashes will be caused by poor understanding by human drivers of HDV intentions, deliberate “bullying” of AVs by human drivers during road operations, unsafe maneuvers by human drivers under their assumption that the AVs will compensate for their errant driving (it is easier to offend a machine than to offend another driver). Then, over time, crashes will decrease due to (a) increased volumes of AVs compared to HDVs, (b) increase in dedicated lanes for AVs at corridors with persistent crashes due to DHV-AV interactions, (c) greater mutual understanding between HDVs and AVs of their driving patterns (AVs will do this via machine learning of human driving patterns).

From an IOO perspective, the nature of AV market penetration trends is a key issue because it will be a significant factor of the demand for AV-supporting infrastructure, and consequently, the expected impact of the required pace of AV-related road infrastructure investments. At the current time, road infrastructure is designed to serve a HDV traffic environment. As AV market penetration grows and AV traffic become dominant, it will be needed to provide infrastructure to serve mixed streams: HDVs, automated Level 1 to Level 4, Level 5 autonomy), and ultimately, a fully autonomous vehicle fleet. Saeed (2019) recognized that AV technological development will be evolutionary, and therefore, road infrastructure retrofitting will be incremental. Retrofitting will be required to be both proactive and responsive in the sense that it will be not only a cause but also an effect of AV demand.

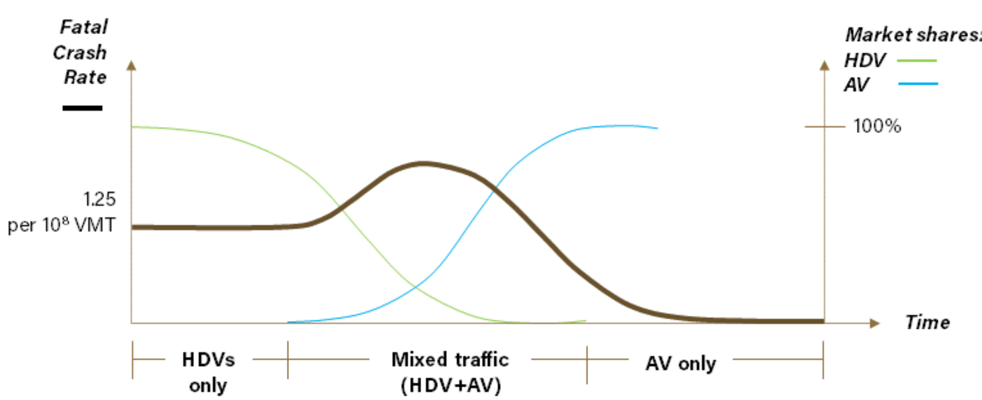


Figure 2.5 Hypothetical AV Safety bump during the transition mixed-traffic period (Labi, 2023)

2.5 The Role of Traffic Safety Requirements

Globally, road crashes cause, on an annual basis, roughly 1.5 million fatalities, 40 million serious injuries, and $230 billion economic loss, besides the large medical expenses and emotional pain suffered by the families of accident victims. The unending irony of this situation is that over 90-95% of highway traffic crashes are not only avoidable but also mostly due to human error (NHTSA, 2016).

A promising solution to this persistent problem is vehicle connectivity and autonomy. By carrying out the driving task, Autonomous Vehicles (AV) are expected to eliminate or reduce human driving error. This is because AVs use verified detection technologies including camera, and lidar to reliably characterize roadway environments and use AI for vehicle control. Therefore, they are devoid of human's adverse states (inebriation, somnolence, drug effects, inexperience, inattention, carelessness, etc.) that promote unsafety. Due to their far lower scope and intensity of human control of the vehicle compared to human driven vehicles (HDVs), AVs continue to generate widespread interest among proponents of enhanced highway safety.

Paradoxically, vehicle autonomy, for all its prospective safety benefits, could pose a two-edged sword: under certain circumstances, the non-human nature of the vehicle operations could be inherently risky. As such, human operator assistance will still be needed to take over the vehicle from the automated system where and when warranted, particularly at irregular and unexpected conditions of the traffic environment. This means that AV operators will need to possess quick and appropriate decision-making reaction capabilities regarding human takeover of the AV. That way, safety and mobility will not be unduly degraded.

The safeness of the AV-to-human takeover hinges on the type and level of assistance that are needed from the human operator. This is expected to be a function of the existing stage of the HDV-CAV transition phase and the expected level of human cognitive input during the driving operation. Regarding trained operators, their input is expected to be adequate, and the transition is expected to be smooth. Current efforts in this regard include comprehensive integration (by automobile engineers) of human driver capabilities into the automation algorithm. This is expected to promote human-centered AV design and real-world operability (Stanton & Edworthy, 1999).

Therefore, the effect of human interaction with automation technology is currently a subject of great interest in the literature. Research, it seems, has mostly focused driving environments and the effect on AV driving tasks with assumptions of complete vehicle autonomy (zero human interaction) and complete reliance on automation (Stanton & Marsden, 1996).

CHAPTER 3 THE CONCEPT OF SITUATIONAL AWARENESS IN THE CONTEXT OF AUTOMATED DRIVING

3.1 SA Definitions and Literature Review

Situational awareness (SA) is the understanding of the elements of an environment in a specific context, so that effective decisions can be made efficiently in terms of time, safety, comfort, and so on. In this study, that context is manual takeover of automated driving. Situational awareness is described as the outcome of situational assessment, and therefore, is only as good as the process used for the assessment. The elements of SA may vary, and SA may change with respect to time, location, or other factors. Table 3.1 presents some definitions of SA in the literature.

Table 3.1 Definitions of Situational Awareness

Definition	Source
"The knowledge of current and near-term disposition of both [opportunities] and [threats] within [an operating environment]"	Hamilton (1987)
"Keeping track of the prioritized significant events and conditions in one's environment (from: Aerospace Glossary for Human Factors Engineers)"	Oliver (1990)
"The knowledge, cognition and anticipation of events, factors and variables affecting the safe, expedient, and effective conduct of the mission."	Taylor (1990)
"One's ability to remain aware of everything that is happening at the same time and to integrate that sense of awareness into what one is doing at the moment.	Haines & Flateau (1992)
"Continuous perception of self and the vehicle in relation to the dynamic environment of vehicle operations, threats, and mission, and the ability to forecast, then execute tasks based on that perception."	Carol (1992)
"Continuous extraction of environmental information, integration of this information with previous knowledge to form a coherent mental picture, and the use of that picture in directing further perception and anticipating future events."	Dominguez (1994)
"The perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future."	Endsley, 1995
"An adaptive, externally-directed consciousness that has as its products knowledge about a dynamic task environment and directed action within that environment."	Smith and Hancock, 1995

The term "situational awareness" has achieved celebrity status at the current time. In the literature, it has been stated that the notion of being aware of your surroundings in an adversarial or collaborative environment, has been around for several centuries, as it is found in documented history of formal military theory and Sun Tzu's classic piece "The Art of War." Hartman and Secrist (1991) stated that "situational awareness is principally (though not exclusively) cognitive, enriched by experience." SA research and applications in the context of transportation have primarily been in the aviation field. SA applications in automated land-transportation vehicles have burgeoned in recent years. Tenny et al. (1992) cautioned that situational awareness contributes to good performance, but the two terms are not synonymous. Therefore, it is possible to have good SA and still not be a good operator of an automated system, and this could be due to poor coordination and motor skills, for example. On the other hand, it is possible to have good driving performance with very little situational awareness, and this could happen particularly where the operator is experienced and operating the vehicle comes as second nature.

Endsley et al. (1998) proposed three hierarchical "levels" or scopes of SA: (a) perception, (b) comprehension, and (c) projection. In the sections below, various terms reflecting the original context (aircraft operations) have been replaced by the context of AV operations.

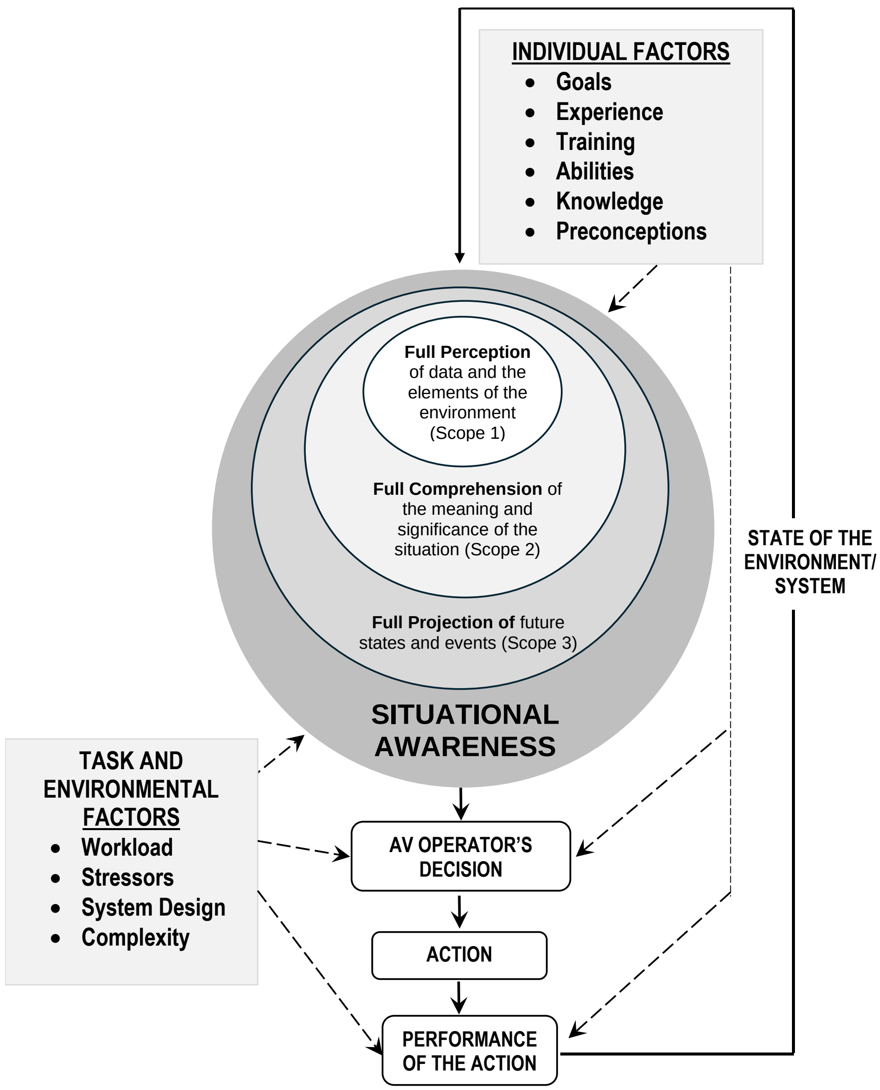


Figure 3.1 A situational awareness model (adapted from Endsley, 1995)

3.2 Scopes of Situational Awareness (Endsley, 1995)

In this report, we use the term scope instead of the term "level" that was used in the Endsley (1995) study to represent what is arguably, the scopes of Situational Awareness. This is because we seek to avoid confusion with the SAE levels of automation.

Scope 1 Situational Awareness (Perceiving the elements of the current roadway/traffic environment)
SA Scope 1 covers the perception of various characteristics of the key aspects of the roadway and driving environments: the locations and dynamics. Details include the locational and dynamic attributes of the vehicle (location, relative locations to other stationary or moving objects, its movement speed, acceleration, and direction), weather conditions, roadway clearances, emergency information, and other relevant aspects of the roadway, roadside, and traffic environment.

Scope 2 Situational Awareness (Comprehension of the current relationships between the elements)
SA Scope 2 extends the operators knowledge of their roadway/traffic environment by going beyond mere awareness of the existence of the elements to establish their significance and the relationships between these elements, both from the perspective of the operator's objectives. Therefore, unlike SA Scope 1, Scope 2 involves a synthesis of the disjoint driving roadway environment elements to establish functional patterns among the elements in a way that yields a coherent and comprehensible tapestry of the roadway environment.

Scope 3 Situational Awareness (Projection of the future relationships between the elements)
SA Scope 3 involves building on SA Scope 1 and SA Scope 2, to acquire knowledge of future roadway/traffic conditions through projections of the effect of future actions associated with the elements in the environment. This is done within some spatio-temporal boundaries of Situation Awareness.

3.3 Measurement of Situational Awareness

A situational awareness construct or indicator is defined as a way by which SA could be measured quantitatively or qualitatively. SA indicators can be placed into two broad categories: inferred vs. direct. Inferred (also termed indirect or derived indicators) use established objective metrics of SA based on operator behavior or performance that is observed empirically or through a controlled experiment. Examples include indicators based on eye-tracking and physiological-measurement equipment. Direct SA indicators are typically obtained using a questionnaire survey where respondents are asked to provide a subjective assessment of the SA they perceive. Like in any engineering system assessment, the choice of indicator(s) must be chosen carefully and must be guided by considerations including appropriateness and relevance, cost and effort in data collection, comprehensiveness, and transferability (Labi, 2014). Sirkin et al. (2017) presented metrics or indicators for situational awareness, and these are discussed below.

3.3.1 Indirect Indicators

(a) Eye tracking based indicators: Tracking the eye movements of the vehicle operator could effectively assess the situational awareness at Level 1 SA, as such data provides an objective record of the extant features of the roadway and traffic, or at least, what the operator sees. In other words, there could be a difference between what exists and what the operator sees – laying one's eyes on an object does not necessarily mean that one has fully perceived the object (Drew et al., 2013; Chabris and Simons, 2011). Eye tracking data collection is rather costly, requires specialized equipment and trained personnel, and can be sensitive to ambient conditions including lighting particularly if collected outdoors.

(b) Indicators based on Physiological Measures: According to Brookhuis et al. (2001) (and subsequently echoed by Sirkin et al. (2017)), the use of attentional resources for SA assessment increases cognitive workload, and that it is much more difficult to assess the deeper situation awareness levels of perception and projection of a driving environment.

3.3.2 Direct Indicators

The Subjective Ranking Technique (SART) indicators of assessing situational awareness involve ranking by the driver or an observer. SART presents a subjective measure of driver SA and needs modification so it can be adequately applicable to non-experts in a driving context (Sirkin, et al., 2017). Subjective rankings obtained from observers could yield SA measurements that are unobtrusive. Further, it has been argued that SART rankings can be used during live action evaluation but require several subject matter experts to review participants' behaviors. Therefore, the reliability of the results could be questionable (Salmon et al., 2006).

The Situation Awareness Global Assessment Technique (or SAGAT), provides popular situational awareness assessment indicators. SAGAT involves stopping a simulation in progress and requesting the human subject to provide their perceptions regarding a specific activity in the simulation environment, for example, the location/position, type, and future status of elements in the environment (Endsley, 1995; Sirkin et al. (2017). Obviously, such frame freezing cannot be used in tests on real in-service roads. Further, this method's intermittent stoppages may jeopardize the human participants sense of presence and immersion in the simulation, thereby potentially compromising the simulation integrity and ecological validity of the study (Lee, 2004; Sirkin et al., 2017).

Question probes provide direct and objective measures of elements perceived in an environment. However, it has been stated that this method could also be used to carry out SA assessment at SA Levels 2 and 3. According to Sirkin et al. (2017), best practices for this technique are inherent in Tremblay (2004)'s Situation Present Awareness Method (SPAM). SPAM's question probes are considered far less intrusive compared to SAGAT's frame-freezing method and are applicable in real-world environments in real time. Mok et al. (2015) cautioned that the probe needs to be designed carefully, to (a) avoid drawing the driver's attention to elements of the environment, (b) avoid undue cumbersomeness, (c) avoid driver distraction and hence impaired their ability to carry out their primary task. The use of surveys administered after the driving task (Baltodano et al., 2015) helps overcome some of these limitations but their efficacy hinges on the ability of the human participants to recall their driving experience. In cases where the driving task is automated with minimal takeovers, question probes are more feasible to use because the participant (driver) could be responding to the SA questions while the automated system drives the vehicle, thereby boosting the ecological validity of the experiment.

3.4 SA Augmentation via Vehicle Interface Placement Design and Alert Modes: A Review of the Literature

The design and evaluation of vehicle interfaces to enhance an AV driver's situational awareness continues to attract researchers who have assessed various interfaces designed to augment SA in AVs. This section presents an overview of vehicle-driver interface development intended to increase the driver's SA in L2 and L3 automated driving systems, as conducted in past studies.

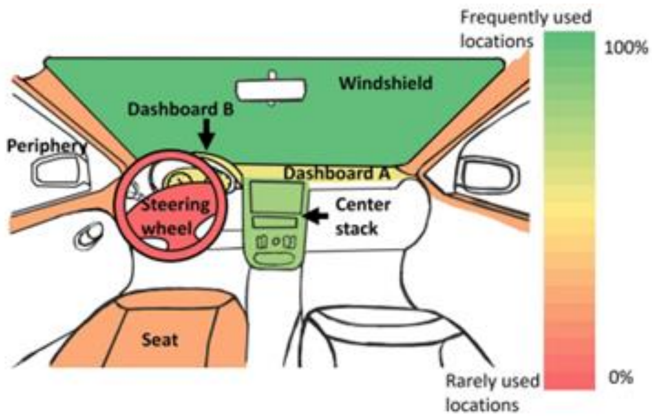
Most of the past studies have illustrated the benefits of deploying driver engagement systems using simulated environments. Schroeter and Steinberger (2016), in a conceptual gamified augmented reality application, presented interactive virtual objects on the driving screen to direct drivers' attention at those locations while their Level 2 and Level 3 AVS engaged. It seems, however, that the researchers did not present experimental evidence of the application's efficacy to increase drivers' situational awareness. Capalar and Olaverri-Monreal (2018) used periodic visual stimulus (i.e., color-changing LED lights) in a driver's peripheral vision to evaluate their response time to takeover requests. Pradhan et al. (2019) used a multimodal system in Level 2 AVS (haptic, visual, and auditory warnings) if the driver is visually distracted (i.e., not looking at the road for 3 consecutive seconds in a rolling 30-second interval) or a takeover is required. It seems, however, that a common shortcoming of these state of the art (SOTA) alert systems is their limited ability to continuously maintain drivers' situational awareness in dynamic traffic environments.

<u>Alert modes:</u> In past research, four categories of takeover alert modes have been investigated:

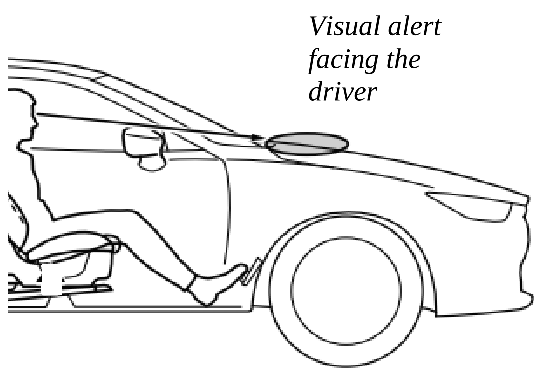
- Auditory: speech, chime, music
- Haptic: pressure, vibration
- Visual: text, light, video, images (icons, symbols)
- Olfactory.

<u>Alert equipment/outlet locations:</u> According to Capallera et al. (2023) and other sources, the typical locations are (Figure 3.2(a)):

- Windshield
- Center stack (horizontal, vertical)
- Dashboard location A (above vertical center stack, beneath the windshield)
- Dashboard location B (left position directly facing the driver)
- Periphery (side mirror, rearview mirror)
- Cabin floor, steering wheel (behind wheel, facing the driver)
- Driver's seat
- On hood of the car directly facing the driver (Figure 3.2 (b))
- On the driver, for example, a wrist-borne device
- Other locations inside the car.



(a) Frequency of mode locations (Capallera et al., 2023).



(b) Potential location on hood

Figure 3.2. Alert mode locations.
(Source: https://www.macx3.net/mazda_cx_3_adjusting_the_driver_s_seat-13.html)

<u>Class of information conveyed by the alert</u>: Most of the information for which an alert is triggered is related to the following:

- The ego vehicle itself (its location, status, intentions such as excess speed, closeness to lane-marking (lateral), longitudinal closeness to a leading vehicle, ego vehicle in another vehicle's blind spot),
- External factors (traffic, other users such as vehicle or pedestrians, temporary obstacles, or hazards, for example, congested traffic ahead, another vehicle in ego vehicle's blind spot)

Table 3.2 (adapted from Tran et al., 2021) presents the SA alert mode types and locations that have been investigated in the literature. Evidently, the most common location is the windshield while the least common location is the steering wheel. The table also presents the multiplicity (single vs. multiple) and dissemination locations of the alerts. Regarding the use of single modes, most of the alerts investigated in past studies have been conveyed via the windshield using visual modes for example, icons or text. Regarding the visual-light mode, locations have included the windshield (Schmidt and Rittger, 2017; the dashboard (Faltaous et al., 2018; Wang et al., 2017; Ulahanna et al., 2020), the center stack (Locken et al., 2016), the steering wheel (Mok et al., 2017), the peripheral pillar (Locken et al., 2016), and the driver (Veen et al., 2017).

Visual text alert via windshield and center stack dissemination was investigated by Lindeman et al. (2018), and Sirkin et al. (2017) and Kim et al. (2019) respectively. Studies have used visual icons displayed via the windshield (Stockert et al., 2015; Wulf et al., 2014; Lindemann et al., 2018; Pokam et al., 2019) and via dashboard (Ulahanna et al., 2020; Beller et al.,2013; Sirkin et al., 2017; Wang et al., 2017; Kim et al., 2019). Interior locations have been found to be most effective for auditory alerts (Nees et al., 2016; Wang et al., 2017). Haptic alerts were used by Telpaz et al. (2015) and Sonada and Wada (2017), and Yusof et al. (2017).

Regarding multiple modes, interesting combinations have been tested for their efficacy in providing situational awareness. Audio-visual interactions (e.g., text/icon and a chime) are also common. Studies that used chime and/or speech icons and/or text (a) through the windshield or through the entire interior (Tijerina et al. (2016), Wulf et al. (2013), Kim et al. (2017), Wiegand et al. (2018), Naujocks et al. (2017)) (b) through the dashboard (Wiegand et al., (2018), and Gang et al. (2018)) and (c) through the center stack (Large et al. (2019), and Beukel and Vort (2017)).

Studies that used chime, speech, icon, light, and physical movement via dashboard alert locations, include Zihsler et al. (2016). Wulf et al. (2013) used video via the vertical center stack. Studies that used haptic (vibration), icons and light have used a variety of locations: the dashboard (Kunze et al., 2019), the vertical center stack (Kunze et al., 2019), the peripheral pillar (Kunze et al., 2019), and the driver’s seat (Kunze et al., 2019).

Table 3.2. SA alert mode types, multiplicity, and dissemination locations (adapted from Capallera et al., 2023)

Uni-modal – Visual

	Windshield/ HUD	Dashboard A	Dashboard B	Center Stack (Vertical)	Steering Wheel	Periphery (Pillar)	Seat	Driver	All Interior
Light	Yang et al., (2018), Schmidt and Rittger (2017)	Faltaous et al., (2018), Wang et al., (2017)	Ulahannan et al., (2020)	Locken et al., (2017)	Mok et al., (2017)	Locken et al., (2016), Karijabto et al., (2017)		Veen et al., (2017)	
Text	Stockert at el., (2015), Lindermann et al., (2018)			Sirkin et al., (2017) Kim et al., (2019)					
Icons	Stockert at el., (2015), Wulf et al., (2015), Kohn et al., (2015), Lindemann et al., (2018), Pokam et al., (2019)		Ulahannan et al., (2020), Beller, Heesen and Vollrath (2013)	Sirkin et al., (2017), Wang et al., (2017), Kim et al., (2019)					
Video				Kohn et al., (2015), Kohn et al., (2019)					

Uni-modal – Auditory

	Windshield / HUD	Dashboard	Center Stack (Vertical)	Steering Wheel	Periphery (Pillar)	Seat	Driver	All Interior
Chime								Nees, Helbein and Porter, (2016), Wang et al., (2017), Beattie et al., (2014)
Speech								Nees, Helbein and Porter, (2016), Serrano et al., (2011)

Uni-modal – Haptic (Vibration)

Windshield / HUD	Dashboard	Center Stack (Vertical)	Steering Wheel	Periphery (Pillar)	Seat	Driver	All Interior
					Telpaz et al., (2015)	Sonada & Wada (2017), Yusof et al., (2017)	

Multi-modal – Auditory and Visual

	Windshield/ HUD	Dashboard	Center Stack (Vertical)	Steering Wheel	Periphery (Pillar)	Seat	Driver	All Interior
Chime and/ or speech + icons and/ or text	Tijerina et al., (2016), Wulf et al., (2013), Kim et al., (2017), Wiegand et al., (2018), Naujoks et al., (2017)	Dashboard A: Wiegand et al., (2018) Dashboard B: Gang et al., (2018)	Large et al., (2019), Beukel and Voort (2017)					Tijerina et al., (2016), Wulf et al., (2013), Kim et al., (2017), Wiegand et al., (2018), Naujoks et al., (2017)
Speech chime, icon, light, physical movement		Zihsler et al., (2016)						
Video			Wulf et al., (2013)					

Multi-modal – Haptic and Visual (Vibration icons and light)

Windshield / HUD	Dashboard A	Dashboard B	Center Stack (Vertical)	Steering Wheel	Periphery (Pillar)	Seat	Driver	All Interior
		Kunze et al., (2019) icon	Kunze et al., (2019) icon		Kunze et al., (2019) light	Kunze et al., (2019) vibration		

Multi-modal – Visual auditory and haptic (Icon/ text, vibration, and chime)

Windshield / HUD	Dashboard A	Center Stack (Vertical)	Steering Wheel	Periphery (Pillar)	Seat	Driver	All Interior
							Okamoto and Sano., (2017)

CHAPTER 4 HUMAN-TAKEOVER-OF-AV: FACTORS THAT INFLUENCE THE NEED FOR SITUATIONAL AWARENESS

4.1 Introduction

As discussed in Chapter 2, the Society of Automotive Engineers classifies vehicle automation in six levels: level 0 to level 5 with level 0 and level 5 being fully human-driven and fully automated, respectively (SAE, 2021). Vehicles having these features are classified as having Level 2 automation, also termed partial automation. Level 3 vehicles, also known as conditionally automated vehicles, possess more advanced driver assistance features and can perform all the driving functions. Regarding these levels of automation, vehicle manufacturers continue to incorporate increasingly advanced features of driving assistance systems, including adaptive cruise control, collision warning, lane keeping assistance, and emergency braking.

With conditional automation, the driver can engage in certain types of tasks that are not related to the driving tasks. Nevertheless, it is still necessary to have a driver in conditionally automated vehicles because the automation system has limitations and will occasionally require the driver to take over the vehicle control when the automated driving system reaches its limit or where the system fails. Such scenarios may include severe weather conditions, degraded lane markings, and sensor failure to recognize a stationary object on the road (Ghasemzadeh & Ahmed, 2013; Wiedemann et al., 2018). Many of the sensors used by an AV for its operation (such as, radar, lidar and cameras) often encounter diminished reliability and functionality under extreme weather conditions (Rasshofer et. al, 2011; Cord and Gimonet, 2014). For example, in severe rain conditions, radar sensors often experience loss in accuracy by up to 45% (Zang et. al., 2019). In such conditions, the vehicle issues a takeover request (TOR), alerting the driver that they need to take over control of the vehicle from the ADS.

Conditional automation is an important step in autonomous vehicle design as it may be thought of as the boundary between full automation and manual driving. A Level 3 vehicle has an advanced automation system capable of performing driving functions, yet not so advanced that it does not need driver intervention on occasion. This makes Level 3 a good subject for studies on human-machine interaction and interfaces thereof. Level 3 AVs allow for the AV operator to be engaged in NDRTs, therefore, the behavior and attitude of Level 3 drivers towards automation may vary based on their distraction level and trust in the system. Due to these expected variations, there is need to study how drivers will react to takeover requests under different alert modes, NDRTs and other factors.

This chapter begins with a discussion on takeover concepts. Section 4.3 is dedicated to risks in the driving environment, i.e., the factors that necessitate a takeover request. These include the road environment, roadway design and traffic conditions. The section also discusses the driving risks arising from passenger behavior and attributes (such as NDRTs, driver impairments, fatigue) and how they affect takeover performance and response time. Section 4.4 discusses takeover warrants. These are combinations of risk factors that necessitate a takeover request and their thresholds thereof. They include rainfall, snow, or hail that impede sensor function, levels of lane marking degradation beyond which the vehicle may not recognize the lane, boundaries, and so on.

Section 4.5 addresses alert designs and modalities which explore the typical ways in which takeover alerts are delivered to the AV driver and the effectiveness of each alert. This section also considers predetermined time budgets and how the allocated time affects the takeover performance and quality. Section 4.6 reviews the propensity of an AV operator to take over the vehicle control, and focuses on the level of trust, learning effect, and situation awareness. In Section 4.7, we discuss SA as a function of several factors. Section 4.8 reviews techniques and methods that are used to model takeover response times.

4.2 Takeover Concepts

Takeover performance can be measured from two perspectives: takeover time and takeover quality. Takeover time can be described as the time elapsed between when the driver receives the TOR and when the driver responds to it by taking the necessary action. Takeover quality assesses features including the time to collision (TTC), number of collisions, driver aggressiveness when braking, lateral deviations, etc. (Körber et al., 2016; Favarò et a., 2019).

Another aspect that has been considered in the literature is the effect of road obstacles (Cohen-Lazry et al., 2019; Tanshi & Soffker, 2019; Wiedemann et al., 2018). Several scenarios have been established to study the impact of different obstacle types on TOP, crash-avoidance, and lane-change performance. Some of these scenarios are:

- crash avoidance with/without lane change possibility when a vehicle is on the road shoulder (Wiedemann et al., 2018),
- caution due to the presence of stationary vehicles in the left lane that block the view on pedestrians that may be crossing the road (Vlakveld et al., 2018),
- takeover performance evaluation via crash avoidance/lane changes in the presence of different types of stationary obstacles on the road (e.g., fallen tree, stopped vehicle, etc.) (Tanshi & Soffker, 2019), and
- the performance difference between the stationary obstacle and the moving-bottleneck (a slow-moving vehicle) scenarios (Tanshi & Soffker, 2019).

4.3 Risk Factors (Inputs)

Conditionally automated systems are limited in their capabilities and thus require sustained human attention and intervention as the system reaches its limitations in any driving situation. This transition must happen in a timely and safe manner. It is therefore essential to estimate the level of risk and driver reaction times in different circumstances to design the optimal time budget. Examples of situations that may affect a driver’s reaction time and takeover quality include: the road environment, traffic conditions, and driver attributes.

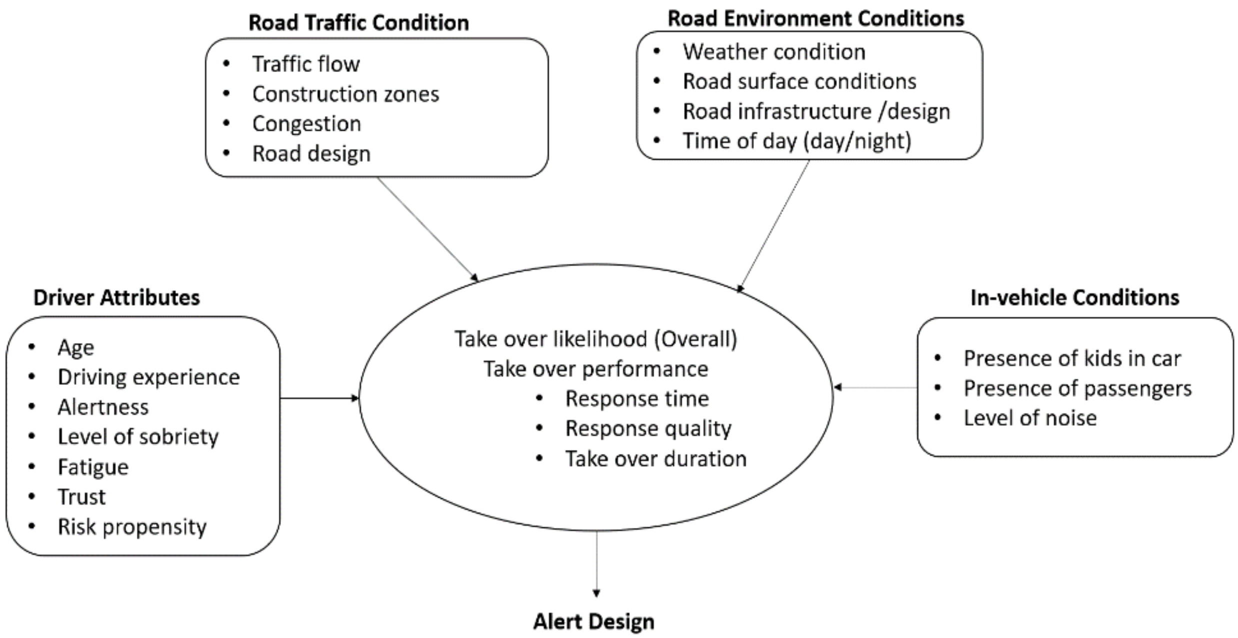


Figure 4.1 Risk factors associated with TO that influence TOP and alert design to promote SA

4.3.1 Road environment

Several researchers have studied the effect of road environment factors on takeover performance and time. These include weather, pavement surface, lane marking condition, and the presence of construction zones. Weather condition was found to be a significant factor of an AV's detection capability of lane markings (Bahram et al., 2015; Zang et al., 2019; Tyler et al., 2019). In 2020, Waymo announced that it will start testing AVs on public roads in Florida to gain further experience on the efficiency of AVs in heavy rain.

Such inclement weather conditions affect the image quality of AVs' sensors, and thus negatively affects desired positions of AVs on the highway cross-section (Ghasemzadeh et al., 2013). In a self-reported study, Canadian drivers indicated how they would adapt their behavior in inclement weather conditions and at high speeds such as 90 km/h (Robertson et.al., 2017); the results of the Robertson et al study showed that younger male drivers demonstrate greater acceptance of (and trust in) automation and are more willing to rely on AVs.

Another road environment feature that will affect take-over likelihood (TOL) is the presence of road construction zones. In this regard, TOR scenarios include avoiding physical obstacles (for example, stalled vehicles, large animals, and debris on the roadway) on the road (Cohen-Lazry et al., 2019). These require the AV to change lanes or come to a complete stop (Kim et al., 2017; Vlakveld et al., 2018). These researchers studied TOT timing and the driver's takeover performance in time-critical situations, for example, under different weather conditions, such as the performance of lidar systems and cameras under different weather conditions including rain (Rasshofer et al., 2011; Cord and Gimonet, 2014; Zang et al., 2019).

(a) Snow or rainstorms *(Source: NHTSA.gov)*

(b) Fog conditions *(Source: Katie Mourn, Unsplash)*

(c) Construction work zones
(Source: FHWA.gov)

(d) Roadway obstacles (debris, stalled vehicles, etc.
(*Source: Agustín Lautaro, Unsplash)*

Figure 4.2 Common road-environment problems that influence takeover and need for SA

4.3.2 Roadway design

Road design could influence takeover propensity and thus, the need for SA. For example, the heterogeneity of road design standards across states or other jurisdictions could lead to inability of the AV perception systems (and associated SA systems) to recognize the requisite vehicle control behavior for safe operations. The use of software trained based on a specific design may lead to the ADS confusion when faced with road designs different from those for which its algorithms were trained (Figure 4.3(a)).

Borojeni et al. (2018) and Brandenburg & Chuang (2019) studied takeover performance and takeover time at curved road sections (Favarò et al., 2019; Naujoks, et.al., 2015). The former found a significant interaction between road curvature and cue urgency on reaction time and the latter suggested that drivers need more time to react to TORs that are presented on curved sections compared to straight sections. This was attributed to drivers showing stronger braking behavior, increased response time, and higher lateral deviation at curve sections compared to straight sections. Wiedemann et al. (2018) also considered a scenario with a double-curve sections (bending sharply to the right and then to the left) (Figure 4.3(b)) and reached a similar conclusion.

(a) (b)

Figure 4.3 Unconventional roadway designs that require high SA (Sources: FHWA; MJT Eng.)

(a)
Wide shoulder (low takeover propensity).
Source: FHWA

(b)
Wide recovery zone (low takeover propensity).
Source: FHWA

(c)
Narrow shoulder (high takeover propensity).
Source: Quora.com

(d)
Areas with traffic-calming designs (high takeover propensity), *Source: Quora.com*

Figure 4.4 Road designs (cross sectional) that may require high SA

Road design speed is also an effective factor of human takeover of the AV and has been considered widely in the literature (Favarò et al. 2021; Tanshi and Soffker 2019). These studies showed that (a) the average drift and offset increase with an increase in speed, and (b) takeover performance decreases when vehicle speed increases. The effect of several other roadway design factors on TOT and takeover performance are worthy of consideration. For example, the number of lanes (Fleskes & Hurwitz, 2019) and shoulder width (Figure 4.4(a)) could affect the driver's takeover performance and decision particularly during certain adverse road conditions such as the presence of road obstacles. Urban road sections designed for traffic calming may require takeover. Further, road designs that are intended for use of the roadway by multiple roads users (for example, vehicles, pedestrians, and cyclists) through demarcated (albeit, closely-located or adjacent) zones for each user class, will require the driver's high alert to avoid collisions with vulnerable road users and therefore, a high takeover propensity, and ultimately, a greater need for situational awareness.

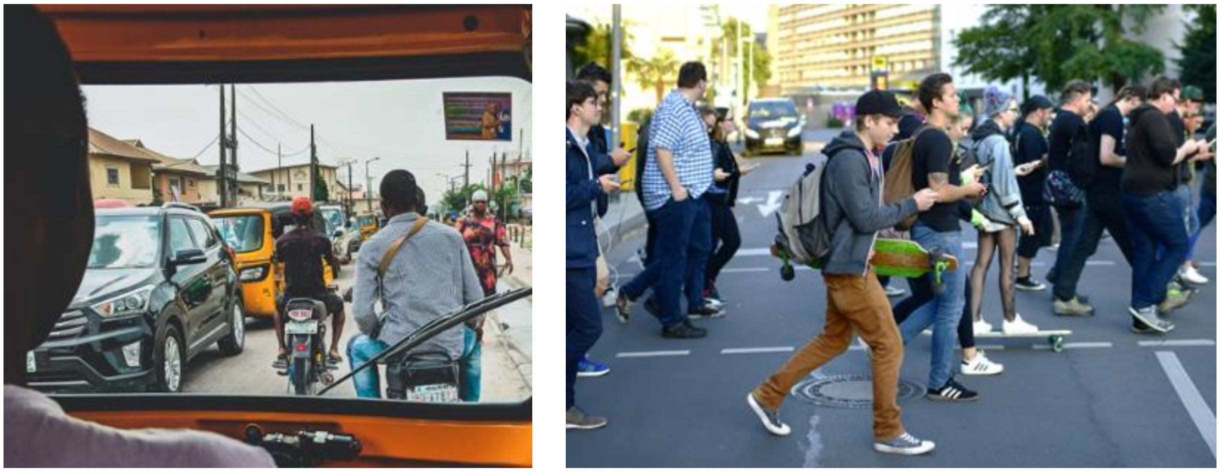
4.3.3 Road traffic operating conditions

Road traffic operating conditions that are most influential of AV operators' takeover propensity includes their awareness of the following: traffic density (which is reflected in the time headway), traffic stream heterogeneity, behavior of vulnerable road users, and the presence of devices that foster communication between the AV and other road users (other AVs, HDVs, pedestrians, and cyclists) in the road environment.

Traffic conditions (particularly in terms of traffic density) affect takeover request propensity, takeover time, and performance (Fleskes & Hurwitz, 2019; Gold et al., 2018; Gold et al., 2014; Körber et al., 2016). This factor has been examined in several ways including studying simulation scenarios with different lanes (Gold et al., 2018). Research has shown that higher traffic density has a stronger influence on crash rate and shorter time-to-collision (Gold et al., 2018). Fleskes & Hurwitz (2019) carried out a similar study and reached a similar conclusion.

Another factor in roadway operations that is strongly linked to increase in crash rate and severity (and decreases takeover performance) is the time headway (Siebert et al., 2014). A recent study (Brandenburg & Chuang, 2019) concluded that time headways should be sufficiently large - at least 0.6 seconds, as a TOR alert is typically issued by automated driving systems when headways fall to a level smaller than this threshold.

The heterogeneity of the traffic stream/ environment, particularly, presence of other road users (e.g., pedestrians and bicyclists) (Figure 4.5(a)) directly affects takeover time and performance. Further, making the decision to cross the street will be more difficult for the pedestrian or bicyclist regarding an AV encounter compared to an HDV (Clercq et al., 2019; Rodríguez Palmeiro et al., 2018). This is because there will be no eye-contact or hand gesture from the AV (Deb et al., 2018).



(a) Dense road use with VRUs (high takeover propensity). *Source: unsplash.com/@joaccord*

(b) Awareness of AVs connectivity to pedestrians via cell phone (low takeover propensity). *(Source: CNN Health online 2/3/2020)*

Figure 4.5 Some traffic conditions that may affect SA

In this regard, several studies have analyzed pedestrian road-crossing behaviors (Razmi et al., 2020; Rodríguez et al., 2018; Velasco et al., 2019) and the effect of human-machine-interface (HMI) in this regard (Ackermann et al., 2019; Gruenefeld et al., 2019; Clercq et al., 2019). Based on the results of these studies (some of which used virtual reality and others used real world scenarios), the pedestrian stress level is affected by vehicle visual features (e.g., magnetic signs on the hood and door, signs on the roof, etc.), vehicle direction (same direction vs. opposite direction), and pedestrians' trust in AV technology. As such, the applicability of informal communication signals between pedestrians and drivers have been studied to identify an acceptable communication method for road crossing when they encounter self-driving vehicles (Ackermann et al., 2019; Gruenefeld et al., 2019).

4.3.4 Distraction of the AV operator

One of the most common factors of crashes is driver inattention, and the effect of inattention can be exacerbated in situations of unfavorable road design and traffic operating conditions. Unlike other factors, driver inattention is difficult to predict and hence difficult to account for in situational awareness assessment systems. Nevertheless, attributes of certain demographics including driver age and state of sobriety, could help predict the probability and severity of driver inattention.

Situational awareness is typically a function of the type of non-driving related tasks being performed. Research has shown that drivers that tend to spend more time looking away from the road and being unaware of their surroundings are at a higher risk and are more prone to slower reactions and higher rates of collisions (Zeeb et al., 2015). For example, active tasks such as writing emails are more distractive compared to passive ones such as watching a video or listening to the news. Thus, more distractive tasks, such as the use of handheld devices as opposed to mounted ones, may cause not only longer reaction times, but also, slower motor response times, slower takeover times, lower overall takeover quality, and more errors such as larger lane deviations at takeover (Zeeb et al, 2016; Zeeb et al., 2017). In such cases, the AV operator's situational awareness is extremely low.

Figure 4.6 Human driver distraction
(Photo credit: National Institutes of Health, www.nih.gov/news)

In driving simulation studies, driving distractions are simulated (and their impact evaluated) using Non-Driving Related Tasks (NDRTs), which are broadly defined as visually or mentally distracting activities that have no relation to the driving task. Such distractions include phone texting, sipping coffee, facial grooming, reading, and talking to other passengers. In experimental settings, these are mimicked using puzzle solving, object sorting, or arithmetic computation. Like the real-life loss of attention, they are designed to mimic, NDRTs cause an increase in mental workload. The mental state and cognitive task load due to driver distractions are typically assessed in a driving simulation laboratory or on the road. This is done by measuring and analyzing the physiological responses of the driver in cases of the driver's takeover of the AV when requested to do so. The driver's mental workload can be assessed through the measured changes in their physiological indicators (heart rate and pupil diameter, for example). By examining these changes, it is possible to measure the correlation between a given task's mental demand and takeover performance. More demanding tasks (such as email writing) have been shown to have greater effects on physiological state and consequently, on the drivers' takeover performance impairment compared to less demanding tasks (Alrefaie et al., 2019).

4.3.5 Driver/Passenger Attributes

(a) Driver impairment

Generally, driving performance is a statement of how well a driver carries out the driving task. Regarding Level 3 automation, the driver is expected to takeover, i.e., resume control of the vehicle when the system reaches its limit. Although the driver is expected to be alert and ready to perform this driving task, this is not always the case. Driver impairments, for example, can and do affect the driver's takeover performance. It is useful to measure the extent to which these impairments affect the driver's performance and how they can be controlled.

Regarding the driver's sobriety state, this could be due to the intake of alcohol, medication, illness, or illicit drugs. The most common threshold for legal blood alcohol concentration (BAC) is 0.08% and driving with BAC above this limit is considered to be unsafe. A study by Wiedemann et al. (2018) suggested that driving at 0.08% BAC level causes increased response time for taking over the driving task from an autonomous vehicle and impairs overall driving performance in terms of lateral and longitudinal vehicle control.

Fatigued or drowsy driving can affect driving performance. Fatigue lowers the driver's alertness and impairs their situation awareness. Also, fatigue induced by lack of sleep causes drivers to react slower to takeover requests compared to fatigue induced by lengthy driving time (Vogelpohl et al., 2019). It is believed that prolonged autonomous driving induces drowsiness in the AV operator particularly if they are not engaged in any non-driving related task. It has been shown that the level of drowsiness remains stable when a non-driving related task is introduced during autonomous driving (Schömig et al., 2015). Driver fatigue could be exacerbated by driving an AV (compared to an HDV), and this could further impair takeover time and performance where other fatigue factors are present in the AV driver. Schömig et al. (2015) found that AV drivers are more susceptible to fatigue compared to HDVs, due to their being less active and lower involvement in the driving process and that AV drivers tend to show signs of fatigue after a short period of driving relative to HDV drivers.

Several researchers have encouraged the introduction of non-driving related tasks into autonomous driving to maintain the driver's situational awareness, and others have suggested the introduction of scheduled manual driving (Wu et al., 2019). Scheduled manual driving has been found to have no effect on younger drivers but affect older drivers. The latter tend to react more slowly during a takeover event in both brake application and turning the steering wheel. Depending on the complexity of the takeover scenario, the time needed to take control of the AV when it reaches its system limits, is affected by drowsiness. Drowsiness does not have a significant effect on takeover times for simple takeover scenarios (Weinbeer et al., 2017).

(b) Driver's age

Compared to other factors, age-related factors seem to have received little attention in the literature. This may be due to an expectation that cognitive sharpness decreases with age, and thus by extension, takeover quality and response times will be longer for older individuals compared to younger ones. There exists limited literature that support this notion; nonetheless, it is universally accepted in studies of other research fields such as psychology.

Two factors that exacerbate age effects are situation complexity and engagement in a non-driving-related-task (NDRT). In a comprehensive study in this field, Körber et al. (2016) used three levels of traffic density (zero, medium, and high) involving younger and older drivers. Also, two scenarios (with and without NDRTs) for each age group were considered, to study the effect of NDRT engagement on takeover performance. The dependent variables in their study were: takeover time (TOT), minimum time-to-collision (TTC), and maximum lateral and longitudinal accelerations. The researchers found no significant difference between younger and older drivers which suggests that despite the expectation of cognitive decline in older participants, they reacted as fast as the young ones.

In terms of takeover time, the study by Körber et al. (2016) suggested that in the absence of secondary tasks and in zero and high-traffic densities (TDs), older drivers have lower takeover time (TOT). However, in a normal (medium)-TD, younger drivers' TOT was found to be lower. Also, the results from the NDRT scenarios suggested that, in all TDs, older drivers have lower TOT. In addition, the difference between the two groups' TOTs is more obvious in the medium-TD scenario. The results of some other studies on the relationship between driver's age and road design speed (Favarò et al., 2019; Makishita & Matsunaga, 2008; Tanshi & Soffker, 2019) indicated that, in the absence of NDRTs, older drivers are more cautious and exhibit a lower TOT. However, both in manual driving (reaction time) (Makishita & Matsunaga, 2008) and automated driving (takeover reaction time), it was found that older people need more time to react or takeover when a secondary task is assigned.

It has been observed that these study outcomes contradict each other. A plausible reason is the difference between the duration of engagement in the NDRT as the hands-free cell phone conversation using the 20-questions task (TQT) (Körber et al., 2016) was implemented in the entire driving period. On the other hand, the other studies had assigned these tasks from time to time in the driving procedure. This factor is important because getting used to a task could affect the TOT. Another possible reason for the dichotomy in the results is that the NDRT type influences a driver's TOT. Older adults generally are less familiar with technology compared to relatively young adults (Souders & Charness, 2018.). Therefore, NDRTs that involve high technology tasks might affect older drivers to a greater extent compared to the younger ones.

In terms of the relationship between age and takeover quality (TOQ), several studies have been conducted (Wu et al., 2020; Li et al., 2019; Körber et al., 2016). Regarding the effect of engagement in multiple NDRTs on TOQ, (Wu et al., 2020) realized that older drivers had significantly inferior TOR performance compared to the younger ones. They also studied drowsiness after the NDRT engagement and how it affects drivers TOQ.

4.3.6 Availability of in-vehicle assistance systems

The reaction time of AV drivers to critical situations is much lower compared to manual drivers (on average by approximately 2.5 seconds) (Demmel et al, 2019). Vehicle-to-everything (V2X) capabilities could help mitigate this situation in a superior manner compared to locally-based solutions (vehicle sensors). With V2X, the AV can possess information about traffic conditions downstream of its location that it may not be provided by its sensors. Therefore, with V2X, the vehicle alerts the driver more quickly so it can be ready for takeover, thus increasing the chances of a smooth and successful takeover, compared to a vehicle relying on only sensors. Tanshi and Sofrker (2019) proposed a takeover set of rules to assist AV drivers.

However, the typically huge influx of sequential data from a highly dynamic traffic environment could render this approach ineffective due to computational intensiveness. Thus, Katrakazas et al. (2019) proposed a methodology for assessing risk, real-time integration of vehicle-related and network-level collision risk using dynamic Bayesian networks modeling and interaction-aware motion modeling. Their study results suggest that using their methodology, interaction-awareness could be enhanced by as much as 10% in collision-prone traffic conditions.

4.4 Takeover Warrants

Conditionally automated vehicles (Level 3) do not require sustained driver attention. However, SAE requires that a driver be always present and ready to take over control of the vehicle with notice (SAE, 2021). This is due in part to the inherent limitations of the automation system and hence its potential inability to handle unusual driving scenarios. As discussed in the previous sections of this chapter, takeover requests may be prompted by adverse environmental conditions (e.g., severe weather), roadway design (e.g., sharp curves or unidentifiable lane markings) and traffic conditions, or the AVs sensor failure (Dixit et al., 2016). Even more challenging is navigating the urban environment and understanding pedestrian behavior and traffic dynamics (Rasouli and Tsotsos, 2018). The combinations of risk factors that may cause takeover requests and their corresponding thresholds are referred to as takeover warrants.

This section discusses how these takeover warrants affect the takeover process and how they influence the design of the automation system. It is easy to identify the risk factors associated with takeover requests. However, modeling their specific thresholds is challenging because many stem from the inherent limitations of each sensor used, the decision-making algorithms implemented, and specific computational architectures chosen. Currently, most warrants are based on the extent to which a sensor is impaired due to weather. Some of this information may be proprietary to specific vendors and thus not readily available to the public. For this reason, a few researchers have documented the performance of various sensors under different weather conditions. Rasshofer et al. (2011) investigated the performance of lidar systems under inclement weather and Cord and Gimonet (2014) investigated rain effect on cameras. Zang et al. (2019) found that in severe rain conditions, radar detection range could be impaired by as much as 45%.

Although literature is widely available on the various risk levels in the driving environment and the limitations of the sensors typically used in AV operations, there is inadequate literature on comprehensive and systematic discussions on combining these factors and determining their thresholds. Researchers with the requisite infrastructure will need to study and establish takeover warrants. To assess the thresholds for takeover warrants, researchers may need to look beyond only the sensor-weather relationship and consider other conditions. For example, what levels of retro reflectivity for pavement markings will be too low for an AV to detect. Additionally, varying the complexity of the urban driving environment may also be necessary to ascertain the level of complexity at which the detection systems fail.

4.5 Alert Design Recommendations

Chapter 3 of this report presented a review of alert designs in literature. This section (Section 4.5) builds on that information further, to make recommendations for alert designs that could be included in any system intended to prospectively enhance AV driver's situational awareness. As discussed in the previous sections, in a Level 3 autonomous vehicle, a driver is needed to take over control of the AV when the system automation reaches its limit or fails. When this situation happens, a takeover request is initiated, and the driver is expected to respond to it. "Alert design" refers to how the information is relayed to the driver. Properly designed alerts could influence the efficacy of the driver's response to the alert. This section explores different alert designs and their combinations, and the time budget related to the takeover request.

4.5.1 Alert modes

Some of the most common alert designs include auditory signals, vibrotactile alerts and visual alerts. Numerous researchers (Cohen-Lazry et al., 2019; Petermeijer et al., 2017) have investigated how the placement and combinations of these alerts influence driver takeover performance in various settings, including how they impact reaction time and takeover quality. Takeover alerts are typically delivered to the driver through visual cues, auditory signals, vibrotactile feedback, or a combination thereof. Using only one alert mode is referred to as uni-modal alert, while the combination of two or more alert types is referred to as multi-modal.

<u>(a) Uni-modal alert designs</u>

In practice, uni-model alerts are uncommon. In the research literature, they are often paired with other experimental conditions to obtain certain responses, such as directionality of the takeover response (Cohen-Lazry et.al, 2019; Petermeijer et al., 2017) or compared with other forms of alert modes (Kim & Yang, 2020; Petermeijer et al., 2017). In the literature, it has shown that the efficacy of uni-modal alerts is generally significantly inferior to its combinatorial counterparts (Petermeijer et al., 2017).

To increase unimodal alert efficacy, researchers have explored novel ways, such as abstract approaches with flashing vertical arrows which indicate needed longitudinal control of the vehicle and horizontal arrows which signal lateral control, or skeuomorphically, where control mechanisms such as, a visual of a steering wheel indicates a need for lateral control, and brake pedal indicates a need for longitudinal control are displayed (Brandenburg & Chuang, 2019). The difference in the effects of these two approaches on takeover response have been found to be little. The skeuomorphic has been associated with larger maximum decelerations compared with the abstract concept. Researchers have also considered augmented reality concepts, where the visual display shows the driver which sections of road should be avoided or which way to drive. Although the results did not indicate significant differences in the overall takeover time, the takeover quality was found to vary between the two scenarios (Lorenz et.al, 2014).

Another approach considered in the literature is the anthropomorphizing of the auditory alerts, as reported by Hester et al. (2017b). In this, the agents are designed to be either anthropomorphic and helpful for driving, by providing the driver with relevant information such as their speed, proximity to other vehicles, etc., or anthropomorphic but not helpful to driving, providing information that is not relevant to the driving task. Otherwise, the agent was just an ordinary beep. The results showed that the anthropomorphic agent with relevant information helped drivers avert a crash in 4 out of 6 takeover scenarios, whereas the beep and anthropomorphic but irrelevant information agents were able to avoid crashes in only 1 out of 6 cases. Quite expectedly, when no alert is provided, takeover performance was poor at best, and often led to more crashes. The interesting finding however is the effect of anthropomorphizing of the alert agent. This would have significant implications for alert design and is a promising area of research that needs to be explored further.

The literature generally suggests that directionality of a uni-modal alert does not influence the directionality of the response (Petermeijer et al., 2017) and that uni-modal alerts are less effective at conveying the urgency of a takeover request (Kim & Yang, 2020). In addition, this effect is exacerbated only when NDRTs, such as cell phone use, are involved (Yoon et al., 2019). However, anthropomorphizing in vehicle agents although not extensively explored, has shown so far to produce superior results in takeover performance (Hester et al., 2017b). It is worth exploring further how much enhancement could be earned using an anthropomorphized alert compared with other alert modes, under different experimental, and using real-world scenarios. In addition, when visual cues are used, there is need to investigate how the size and positioning of the visual stimuli influences the takeover time and quality.

(b) Multi-modal alert designs

A combination of two or more modalities is referred to as a multi-modal design type. This encompasses everything from a simple combination of two or more visual, vibrotactile and auditory designs, to more complex and abstract designs such as steering wheel transformations and other spatial design considerations. Literature has shown that multi-modal alerts are more effective at conveying the urgency of a takeover alert compared to their uni-modal counterparts. They result in faster response times. Consistently, tri-modal alerts appear to have the best performance, followed by bi-modal alerts and last uni modal alerts (Kim & Yang, 2020; Yoon et al., 2019; Zhou et al., 2020). Moreover, combinations containing vibrotactile alerts produce faster response times than combinations that do not (Huang et al., 2019; Petermeijer et al., 2017).

In some cases, drivers may be alerted about an impending takeover through auxiliary means, in addition to the already discussed alerts. For example, researchers have experimented with a redesign of the steering wheel to allow it fold over during automated driving, and then unfold back to shape right as a takeover request is issued. Although this transformation may take less than a second, the movement and sound made during the transformation is perceivable enough that it acts as an advance alert of an impending takeover. Some researchers suggest that drivers' reaction times are faster in the transforming steering wheel design compared with conventional design (Kerschbaum et.al., 2015), although the overall response time is not significantly affected. An advance warning of reduced system confidence may be given, indicating a takeover may be required but is not yet imminent. This has been shown to improve the driver's situational awareness and improve takeover performance (Tijerina et al., 2016; Van Der Heiden et al., 2017).

4.5.2 Time Budget for the Takeover

Several approaches to alert design have considered changing the time budget and measuring its effects on the driver reaction and takeover performance. It is imperative that the driver is provided adequate time to react to the situation and safely assume control. It has been stated in the literature that depending on the situation at hand, the time budget influences different aspects of takeover performance. In addition, it has been shown that although drivers react faster with a shorter time budget, the takeover quality is generally worse because of rushed decisions (often made on impulse) (Gold et.al., 2013; Kim & Yang, 2017a), and the number of deviations in the lane position at takeover increase with a reduction in allocated time budget (Clark & Feng, 2015). Crash rates increase sharply when the allocated time budget falls below 10 seconds (Wan & Wu, 2018), but time budget does not directly have a significant effect on the minimum or average speed at takeover (Clark & Feng, 2015). Moreover, other critical indicators of takeover performance including the minimum time to collision (TTC), braking and throttle input are influenced not only by the allocated time budget but also by the driver's prevailing NDRT just before the takeover request was issued (Clark & Feng, 2015; Gold et al., 2018; Wan & Wu, 2018).

Table 4.1: Summary of Alert Designs

Alert Design	**Description / Type**	**Summary Discussion**
Mode class of the Alert	Unimodal: comprising of one mode of message transfer, visual, auditory, vibrotactile.	Not used commonly in practice due to limited efficacy, used in research in combination with other factors. Other approaches (abstract representation or augmented reality) showed no significant improvements over traditional types.
	Multi-modal: visual/audio, visual/vibrotactile, etc.	More effective than unimodal alerts, produce faster response times. Combinations that include vibrotactile types produce faster response times than those that do not.
Time budget (TB)	Time allocated for the driver to takeover control of the AV before a collision is eminent.	Shorter TBs lead to quicker reactions but poor takeover quality. Time budgets (TB) below 10s are associated with higher crash rates. TBs do not directly influence the minimum or average speed at takeover.

4.6 Propensity of the AV Operator to take over the Vehicle Control

Driving experience in an automated vehicle may be influenced by several factors that stem from the driver's characteristics, attributes, and attitudes towards automation. Such factors include level of trust in the automation, previous experience and associated learning effects, driver's alertness, and situation awareness. These factors are important because not only do they affect the driving experience, but also influence takeover performance. Studying these factors and their effects may provide insights into how designers could improve autonomous vehicle design, such as restricting certain NDRTs to improve situation awareness. Understanding the user's propensity to take over may also help designers engineer systems that balance the need for trust in the automation with the caution required, and the level of situation awareness.

The propensity of an AV operator to take over the vehicle is typically explained as the operator's tendency to take over control even before a takeover request is initiated. This could be measured based on the alertness of the driver (i.e., how often they gaze on the road during automation) and placing their hand on the steering wheel and their foot on brake pedal. A drivers' propensity to take over is influenced by several factors, including their trust in automation, the type of driver and their situational awareness. These, in turn, are assessed differently depending on the situation at hand, and typically using proxy variables such as pre-emptively putting foot on brake, having hand on steering wheel, etc. Typically, a steering wheel change of 2-degrees or more is widely used as a threshold to measure the likelihood to take over via steering, with any change less than 2-degrees assumed to be used for stabilization of the vehicle by the drivers (Cohen-lazry et al., 2019). A 10% or more brake pedal actuation is often used to define a braking reaction to a request to take over (Gold et al., 2018).

4.6.1 Impact of driver type and their level of trust

The propensity of a driver to take over might be based on the level of the driver's trust in vehicle autonomy and the driver type. Factors that affect the level of trust include the driver's aggressiveness and their age, which is linked to their driving experience. Trust in automation also correlates with reliance on automation. Drivers that trust automation tend to rely more on it, and those that do not trust the automation are more likely to reject it. In the literature, it has shown that software and automation agents that exhibit personality attributes identical to those of drivers or that are anthropomorphic, have a higher tendency of being accepted by AV operators (Hester et al., 2017a; Körber et al., 2018).

It has been shown that the extent to which a driver monitors the road during an autonomous driving process is influenced by the driver's level of trust of an autonomous vehicle (Körber et al., 2018). It has also been shown that the experience (learning effect) with autonomous vehicles increases the level of trust that drivers have in autonomy (Gold et al., 2015). As described by (Marsh & Dibben, 2003) and supported by (Hoff & Bashir, 2015), trust can be categorized as: situational trust, dispositional trust, and learned trust.

Situational and learned trust are derived trust based on the experience of the AV operator with an autonomous vehicle and its environment. Dispositional trust refers to the type of trust which is more stable and likely to affect the AV operator's propensity to take over, as it describes the type of driver (driver aggressiveness). It makes sense that cautious drivers are likely to exhibit a higher level of propensity to take over compared to other types of drivers. Also, a crash may occur if the operator is over reliant on autonomy and fails to pay attention to the driving process. Therefore, it is necessary to ensure a balance.

The driver's age also influences their trust of vehicle autonomy. The driver's experience is generally directly related to his/her age. Older adults have more driving experience compared to younger adults. Older people tend to trust automated decision aids more compared to younger ones. This is because they do not have great confidence in their own driving performance (Ho et al., 2005, Gold et al., 2015). It has been reported that older adults are unable to quickly detect automation failures (Ho et al., 2005).

4.6.2 Driver's learning effect

The learning effect, which is also referred to as repetition effect is closely linked to trust in automation. As stated in the previous section, trust can be categorized under three layers, which includes learned trust. Learned trust refers to trusting the automation after experiencing and becoming familiar with it, and therefore, being able to assess its potential. This learning effect is a crucial component in determining how people will welcome automation as it will influence their willingness to purchase an AV. According to Gold et al. (2018), the repetition of take-over situations could enhance takeover performance. It has been argued that such improvement in takeover performance is significant only for the initial takeover event compared to the subsequent takeover situations (Hergeth et al., 2017).

Moreover, when drivers encounter noncritical takeover situations prior to critical ones, the learning effect could fade out or invert. This happens because drivers would need more time to adapt to the change from a noncritical to a critical takeover situation. Even though this might be true for all models, the driver's age was found to have no influence on such learning effect, as the takeover time (TOT) and minimum time to collision (TTC) decreases for both older and younger drivers (Körber et al., 2016). Happee et al. (2017) also support the argument that when AV operator is more familiar with their AVs the overall driving performance improves because the intervention time (TOT) and the brake reaction time decrease.

4.7 Overall Situation Awareness as a Function of the Factors

Similar to the level of trust, situational awareness also affects the propensity of an autonomous vehicle driver to take over control of the vehicle. A number of research studies have investigated how to get the driver's attention to revert to the road quickly during a takeover request, as this is believed to result in a faster reaction time and improves the overall driving performance. Situational awareness could be impacted by factors such as the duration of the autonomous phase, how fast the driver reverts their attention to the road, the NDRT type during the automated phase and the amount of time available to take over control of the vehicle. How quickly a driver gains situation awareness can affect the overall safety on the road, as the driver may even momentarily fail to consider the safety of other road users and only focus on pending takeover tasks.

Drivers (particularly, those in a fatigued state) that stay too long in autonomous driving mode typically find it difficult to stay alert, (Vogelpohl et al., 2019). For situation awareness, the number of latent hazards that could be spotted depends on how fast the driver's eye reverts to the road and the amount of time available (Vlakveld et al., 2018). However, eyes-on-road is only necessary but not sufficient to ensure higher situation awareness in relation to visual distraction in the case of highly automated driving (Radlmayr et al., 2014). Also, the urgency of the takeover request may not necessarily ensure that the driver gains enough situation awareness within that short period. Borojeni et al. (2018) showed that drivers respond to urgent cues faster only on straight sections. Urgent cues presented on curved sections, resulted in slower response than non-urgent cues.

Situational awareness plays a major role in traffic safety. A driver's alertness and how they interpret information is expected to affect the safety of the ego vehicle and the safety of the other road users. The Revell et al. (2019) study results suggest that during takeover, drivers focus more on the interaction with the system (such as the acceleration of the vehicle) compared to the situation. This means that safety may be compromised if human machine interfaces are not designed to support situational awareness, or if takeover requests are not designed in a way to help the drivers to quickly regain situational awareness. Also, the time available to initiate a manual takeover of an autonomous vehicle affects the level of situational awareness gained. Typically, drivers do not have enough time to gaze at their rear-view mirrors during a takeover request even though they might display faster reaction times (Lotz et al., 2019).

Drivers are more inclined to apply the brakes than to turn the steering wheel or press a special TOR button during a takeover request (Kim & Yang, 2017a). Drivers accept software applications that can lockout NDRT during a takeover request. With the use of task lockouts, it takes less time to get the driver's hands on the steering wheel but does not necessarily change the brake application time (Wandtner et.al., 2018). The two commonly used methods for measuring situational awareness gained during a takeover request are Situation Awareness Global Assessment Technique (SAGAT) and Situation Awareness Rating Technique (SART). The SART has proven to be more accurate compared to the SAGAT (van den Beukel et al., 2013).

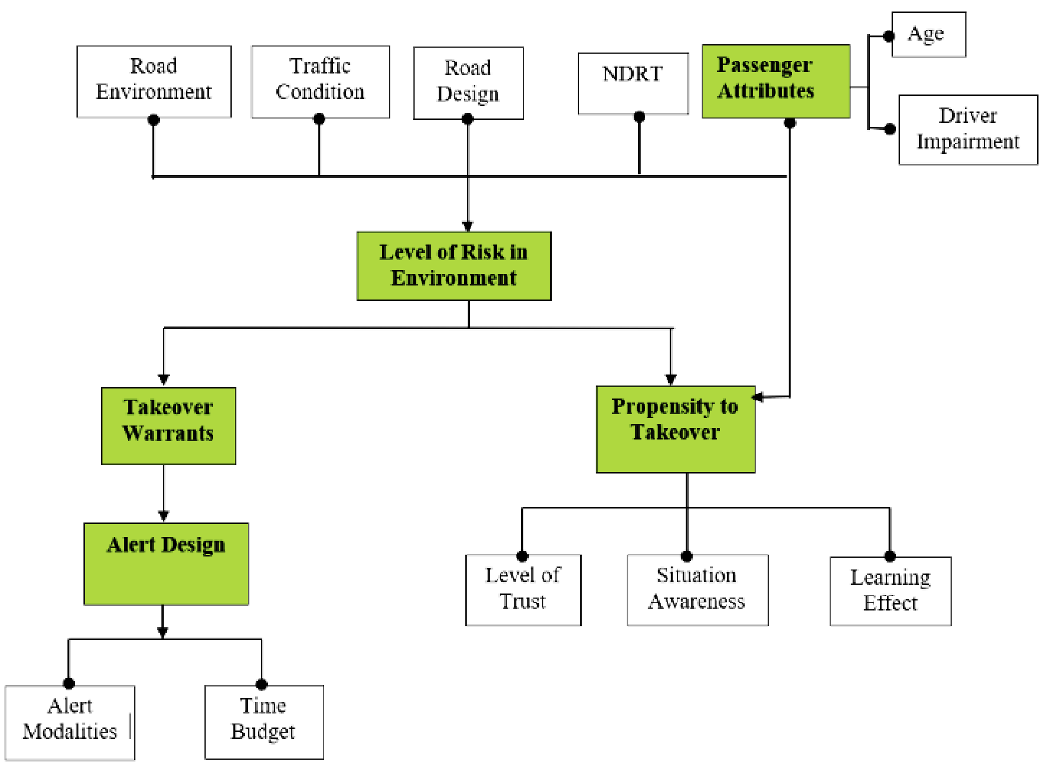


Figure 4.7 Situational awareness in the context of human takeover of AV: Considerations

4.8 Modeling Takeover Performance

4.8.1 Response time

Response time, in the context of human takeover of AV, consists of three separate but sometimes overlapping time segments. The first is the time taken to perceive and register the threat and need for a takeover, often referred to as the reaction time. This is modeled as the time interval from the takeover request to the first perceivable reaction (often, when the driver first gazes on the road ahead to identify the threat, or the time to first glance) (Kim et al., 2018).

The second segment is the transition or motor response time, which is the time immediately after registering the threat. The driver then undertakes a physical action to mitigate the threat by applying brakes or moving the steering. This segment is modeled as the time from the first glance (TTFG) to the first detectable action, either turning the steering wheel through a specified angle (typically 2 degrees), pressing the brake pedal a specified distance, typically 10% of its maximum travel distance (Zeeb, et. al., 2015; Kim et al., 2018) or simply, the time to put hands on the steering wheel, conveniently named the time to first hands (TTFH). The last segment is the settling or stabilization time. This refers to the amount of time taken for the driver to perform the full transition to fully manual control and have the vehicle settle on a normal trajectory. Takeover time is the sum of these three segments. However, depending on the attributes and factors being studied, researchers may use either of the described times as a response time, and often, the distinction is either unnecessary or irrelevant.

Kim et al. (2018) showed that mentally and visually distracting tasks affect only the time-to-first-gaze, i.e., the time to first hands or settling time were not changed. They showed a statistically significant difference in the overall response time between the two tasks compared with a control sample. With regard to the reaction time alone, however, the visually distracting task produced a significantly slower reaction time compared to both the control and the mentally distracting task.

4.8.2 Takeover effectiveness or quality

The effectiveness of AV-to-manual takeover can be measured in terms of the ease of takeover and vehicle jerk during takeover, and the overall safety and mobility of the AV and of the neighboring process in wake of the takeover. Driver takeover performance is important not only for the safety of the individuals on board but also for other road users. Thus far, much of the literature has focused on highway driving scenarios where pedestrians and cyclists may not be an issue.

However, the reality is that AV deployment will inevitably start in cities where pedestrians are ubiquitous. Fleskes & Hurwitz (2019) showed that the presence of cyclists in a driving environment can impact the driver’s takeover performance. Their study showed that upon takeover, drivers were more likely to yield when they spotted a cyclist closer to the stop line than when they thought they were further away. However, the probability of yielding decreased when the takeover time budget was reduced. The literature lacks extended studies on the effect of the presence of pedestrians and other urban elements on takeover performance (because most of these studies focused exclusively on highway driving scenarios).

CHAPTER 5. SAES APPLICATION CASE STUDY: HEADWAY TRADEOFFS IN AV ENVIRONMENTS USING A DRIVING SIMULATOR EXPERIMENT

5.1 Introduction

CAV technologies provide promising solutions to transportation challenges that have plagued transportation systems for decades. Past research findings suggest that CAV adoption can contribute to the enhancement of safety, productivity, and capacity of existing highway transportation corridors (Du et al., 2020). A growing body of research documents the impacts of deploying the V2X connectivity (including vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) to facilitate roadway traffic and environment monitoring, trajectory planning, and path decision making during automated driving modes (Darbha et al., 2018; Jung et al., 2020; Dong et al., 2020; Chen et al., 2021). For example, with V2X communication, CAVs are afforded not only a superior level of situational awareness regarding their surrounding environments but also an opportunity to form platoons that are associated with smaller headways.

One of the expected benefits of V2X capabilities of CAVs is the decrease of headways between successive vehicles in the traffic stream, thereby improving traffic throughput and overall mobility in a road corridor. Large headways improve safety and driver comfort but impair throughput; conversely, when the headways are too small, the AV operator/driver may exhibit discomfort and thus takeover from the automated driving system (Figure 5.1). The research question, therefore, is: what is the best headway that achieves a good balance between secure/comfortable headway versus mobility-enhancing headway?

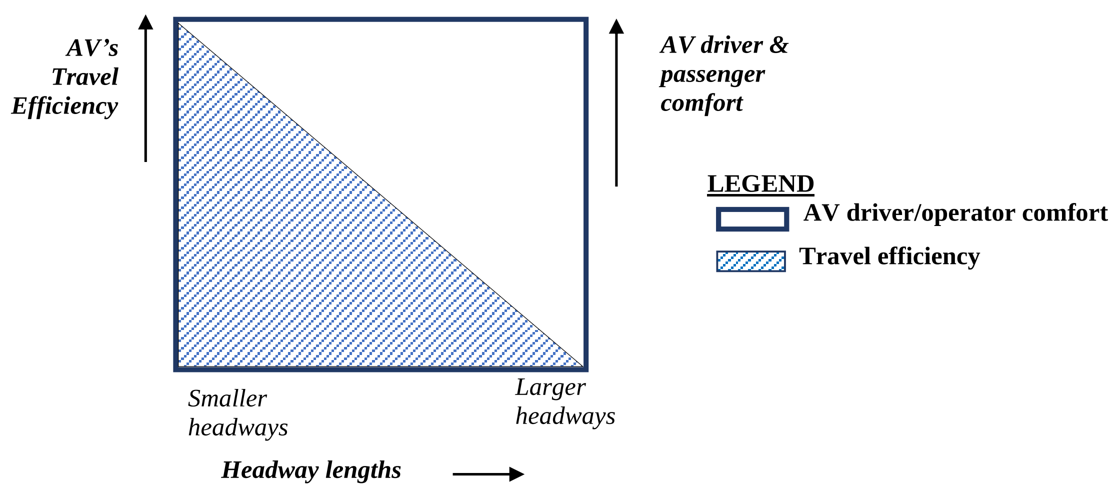


Figure 5.1 Travel efficiency vs. driver comfort – Conceptual tradeoff (Li et al., 2021)

Headway can be expressed in terms of time or distance. The former is the bumper-to-bumper gap from the following vehicle to the lead vehicle in front; the former is the time (often, seconds) that elapses between two consecutive vehicles in a car-following situation (Winsum et al., 1996; Fuller, 1981). Headway can be considered a key measure of road traffic safety hazard in the context of rear end collisions (Vogel, 2003). It has been reported that in countries such as France, Hong Kong, and Netherlands, a 2-second time headway is recommended. In other countries such as Sweden, a lower threshold of 1-second is used (Risto and Martens, 2013; Vogel, 2003).

Regarding the distance headway, Cutting & Vishton (1995) observed that drivers of following vehicles often perceptively estimate the distance to the leading vehicle in front. Figure 5.1 shown earlier in this chapter, suggests that in the context of headway distance (or time), there exists a tradeoff between travel efficiency and the driver's comfort. Risto & Marten (2013) suggest that, in comparison to time headway, the driver's judgment in distance headway could be influenced to a greater extent, depending on travel speed variations and the physical distance between the lead vehicle and the following vehicle. It has been proposed, in the literature, that for safety reasons, a 20-40 veh/km increase in traffic density should be accompanied by a 4–10m reduction in the minimum headway distance (Abuelenin & Abul-Magd, 2015).

Duan et al. (2013) cautioned of the extant gap between minimum safe distance headway and the headway distance that drivers found comfortable. They observed that in experiments where drivers were asked to "keep a comfortable distance," they often maintained longer headways compared to experiments where they were asked to "keep a minimal safe distance." Also, Piccinini et al. (2014) found that even with vehicles equipped with an ACC, drivers still tend to adopt longer headways compared to the group tested with driving without ACC.

Suzuki & Nakatsuji (2015) and Taieb-Maimon & Shinar (2001) observed that the headways preferred by human drivers vary with traffic conditions. This suggests that driving behavior is influenced by the risk perception of drivers. This is supported by the findings in the literature that older drivers tend to drive with longer headways because they generally have higher perceptions of safety risk (Charlton et al., 2006; Ni et al., 2010; Shinar et al., 2005; Andrews and Westerman, 2012; Martchouk et al., 2011). Chen et al. (2019a, 2021a) observed that under when traffic volume is high, experienced drivers tended to maintain greater time headways to reduce crash risks. Also, as established in the literature, driver perceptions and behavior differ across the class of the vehicles they drive or follow on the roadway (Chen et al., 2021b) and that lower headways are associated with higher perceptions of (a) risks of rear-end collision and (b) discomfort and insecurity (Siebert et al., 2014; Lewis-Evans et al., 2010). One of these researchers evaluated the impact of a range of time headways and observed a significant increase in drivers' perceptions of safety risk and discomfort after 2-second headways. Siebert et al. (2014) subsequently identified appropriate time-headway thresholds that correspond to different speeds from 50km/h to 150km/h.

These past studies helped lay a foundation for further investigations into the patterns of driver's headway behavior and preferences. This is important in the current era as society transitions towards vehicle automation and automation-to-human takeover situations. With regard to headway research associated with vehicle automation, previous studies have shown that drivers with low trust in automation generally deactivate automated driving when they encounter the least risk in traffic such as congested traffic characterized by small headways (Petersen et al., 2019; Deo and Trivedi, 2019; Molnar et al., 2018; Hengstler et al., 2016; Miller et al., 2016). Also, driver perceptions and behavior are expected to be different depending on the automation status of the vehicles they are driving and the vehicles they are following on the roadway in a specific instance of traffic flow.

Further, it is important to duly recognize that, in the emerging age of vehicle automation, humans' drivers will have their driving roles change to co-driver or even passenger roles (Elbanhawi et al., 2015). Wright et al. (2019), Merat et al. (2014) and Forster et al. (2017) carried out driving simulator experiments and determined that Level 3 automated drivers tended to take over the vehicle based on a comprehensive but implicit assessment of the traffic and other conditions on the roadway. Payre et al. (2016) argued that the takeover actions, inherently, are indicative of some absence of trust reposed in human drivers regarding the automated driving system and that they perceive ADS only as a backup. In that case, it seems reasonable to argue that in Levels 4 or 5 automation (where there is little or no possibility of human takeover of the driving task), driver and passenger anxiety could be exacerbated, particularly in traffic environments deemed to be risky, such as dense traffic with little headways. As such, it seems essential or, at least, prudent, to assess the driver's needs regarding headway comfortability in the context of AVs.

In the literature, drivers' headway preferences under different driving conditions have been examined to some extent. Yet still, there is limited research on the difference in driver's comfort level between the vehicle-following distance decided by human drivers and that decided by the automated driving system. In the prospective era of a mixed stream (CAVs and HDVs sharing the roadway), the problem will remain as it currently exists. Therefore, it is critical to identify the headway threshold by analyzing the trade-offs between the user-friendly headways (to ensure drivers' comfort level and safety) and smaller headways (to enhance overall mobility) in an automated driving environment.

To address this issue, driving simulator experiments could be carried out to observe driver perception and behavior. In comparison to other platforms for AV testing (such as, in-service roads and test tracks), driving simulators provide a flexible, cost-effective, and safe opportunity to investigate the research question (Boyle and Lee, 2010; Chen et al., 2019a; 2019b; Chen et al., 2021; Fisher et al., 2011). The present study seeks to contribute to the ongoing national conversations regarding headway design in the AV era. The study uses a driving simulator experiment to carry out headway threshold design in the context of CAV operations environment. The experiment takes due cognizance of driver discomfort and takeover intentions, and to provide information useful for characterizing the tradeoffs between mobility-enhancing headways versus safe/comfortable headways in an automated driving environment.

The driving simulator in the present study possesses a Level 3 automated driving system whose features are consistent with SAE standards for that level of automation (SAE International, 2018): requires driver vigilance and readiness for takeover in specific safety-critical traffic situations; and the capability to adopt specified. The latter is also important as smaller headways without considering the driver's perception will cause several unwarranted takeovers; the driver will take over if they feel discomfort or feel that any instance of close car-following is not safe. Also, this study adopted the method of constant stimuli (Simpson, 1988; Gescheider, 1985; Leek, 2001), with slight modification, to measure the quantitative relationship between the driver perception and the stimulus (in this case, the different values of the distance headway).

The study described in this chapter was carried out at Purdue's CCAT/NEXTRANS Driving Simulation and Human Factors Laboratory located at Kent Avenue in West Lafayette. The study used the same experimental settings as another similar parallel study. The experiment described herein in this report used the same resources and at the same time as the other experiment. The other study, however, focused on trucks as vehicles while the current study focused on automobiles.

The remainder of this chapter is structured as follows. Section 5.2 provides details of experimental design, procedures of driving simulator test and the method of analysis. Sections 5.3 and 5.4 present the results and discussions, respectively. Section 5.5 concludes the chapter with a summary of the findings and future research directions.

5.2 Study Methodology

5.2.1 The Human Subjects

The human subjects for the headways experiment were voluntary participating students enrolled at Purdue University during the study period, had a U.S. driving license, and were in a good state of health (self-declared). The experiment followed Purdue's IRB guidelines, and the researchers sought and obtained IRB approval. Each participant provided their informed consent. Participants were screened prior to the conduction of the experiment and were required to: have had adequate sleep the night prior to the experiment; have abstained from consumption of caffeinated beverages and alcohol 24 hours prior to the day of experiment; and be fully sober and conscious at the start of the experiment, depending on the level of caution they stated to exercise, the participants were grouped as follows: when driving normally: high-confidence (Group 1); moderate or neutral confidence (Group 2), and cautious (Group 3).

5.2.2 Equipment and established scenarios of driving task

A fixed-base driving simulator was used for the experiments. This simulator has 3 screens, a dashboard, a steer with force feedback, and pedals for the clutch (in case of manual gear control), the brake, and the accelerator). The simulator has control buttons for various functions including turn-signal and headlight, gear mode shift (manual-automatic transmission), and a sound system. The driving simulation environments and scenarios were designed using SCANeRTM studio software, and the simulation environment used is a straight section on the Interstate 465 corridor in northern Indianapolis. The simulator is capable of easily transitioning between autonomous and manual driving modes and is useful in situations where the participant seeks to transition from automated to manual mode where the participant deemed the extant headways to be unsafe or uncomfortable during the driving process. The driver's levels of discomfort were also measured using a questionnaire survey.

5.2.3 The Experimental Process

The first step in the experiment was to carry out a practice run (that is, pre-test participant training). This facilitated driver familiarization with various control functions and modes of the driving simulator (including autonomous driving activation) and to ascertain whether any prospective participant was prone to simulator sickness. The participants were informed that they bore the responsibility for monitoring the system performance and to transition to manual mode anytime they felt such a switch was warranted. Instructions were also given on weather conditions (which could interfere with signals from sensors), lane-marking conditions and the presence of construction zones. Where the vehicle encounters road or traffic conditions it cannot handle, it issues a request for the driver to take over control of the vehicle. The simulators' automated driving system can make a takeover request at any time during the drive. However, the driver is fully responsible for ensuring complete situational awareness of the extant traffic conditions.

Regarding the manual-driving session, participants completed ten tests in the manual driving mode. In each test, the drivers made manual control adjustments to maintain comfortable following distances between themselves and a leading vehicle and were asked to switch from manual driving to automated driving when (in their opinion), a "comfortable" level of headway had been reached. These thresholds mean values (μ) and standard deviation (σ) were determined.

Regarding the automated-driving session, five headway levels were set to $\mu-2\sigma$, $\mu-\sigma$, μ, $\mu+\sigma$, $\mu+2\sigma$. The vehicle was set to follow the leading vehicle with a predefined headway. The 5 distance headways served as the "stimuli". For each of these headways, fifty tests were carried out (thus, 250 observations in total). The stimuli were randomized and counterbalanced across the participants. At the end of each test, the participants answered "yes" or "no" to the following questions: (a) Q1 – Did you experience any discomfort? Y/N, and (b) Q2 – Did you have a desire to take over the vehicle? Y/N. Question 2 was posed to the participants only when the response to Question 1 was affirmative.

This experiment collected data on the levels of drivers' discomfort and not their comfort levels. This is because (a) the results of the pilot study suggested that drivers are generally more sensitive to discomfort than they are to comfort, (b) a benefit of CAVs is the opportunity to operate at smaller headways compared to traditional vehicles; because drivers tend to feel more uncomfortable with distance headway reductions, it is more intuitive to measure their discomfort. The 3 discomfort levels defined are: Very uncomfortable, Somewhat Uncomfortable, and No discomfort.

- Where the participant response to Question 1 as "No", it was then noted that the headway in question posed No Discomfort.
- Where the response to Question 1 was "Yes" and the response to Question 2 was "No", it was then noted that the headway in question posed a little discomfort, that is, Somewhat Uncomfortable, and,
- Where the response to Question 2 was "Yes", the headway in question was noted as 'Very Uncomfortable'.

Figure 5.2 presents the overall procedure for measuring the headway thresholds. Figure 5.3 illustrates the relationship between headways and level of discomfort. Using the method shown in Figure 5.4, this study developed a relationship between the stimulus (distance headways) and driver's discomfort level.

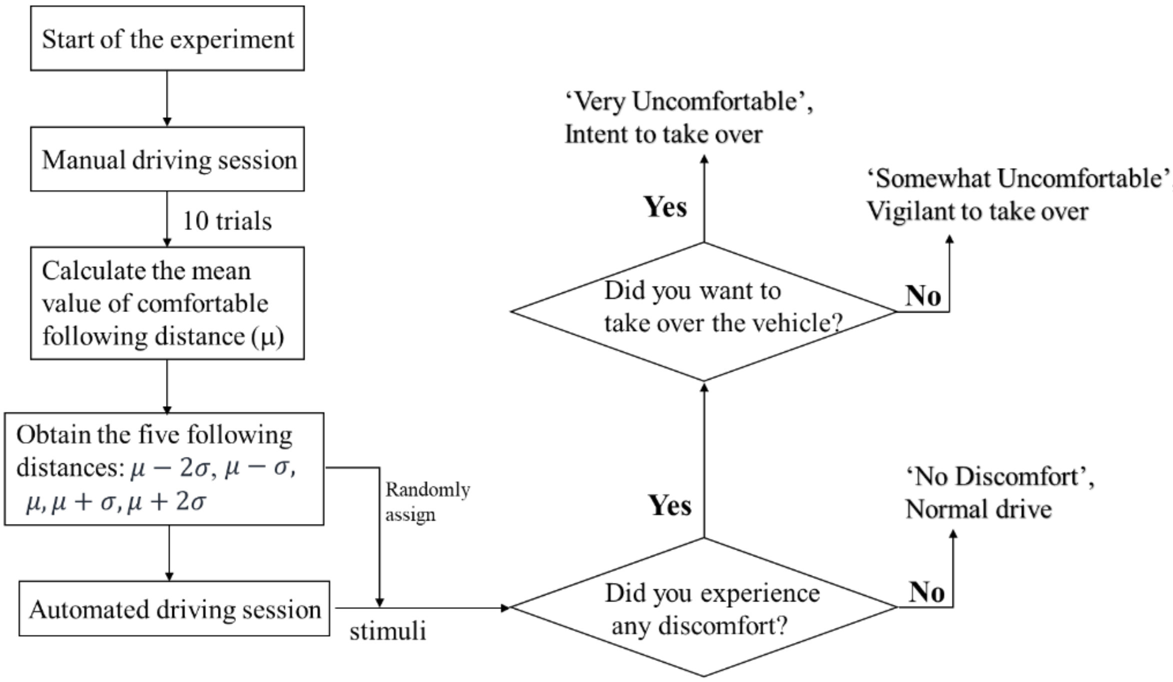


Figure 5.2 Steps for the headway threshold determination

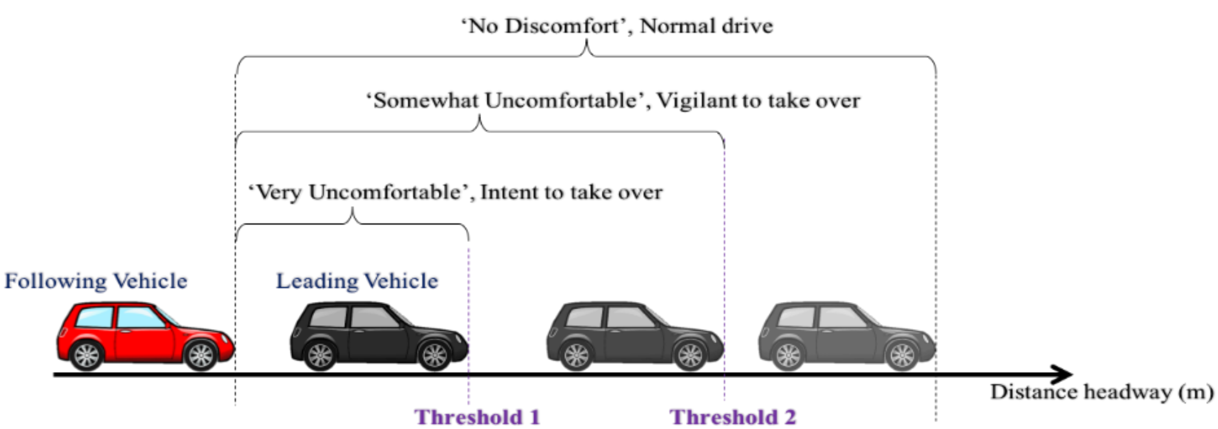
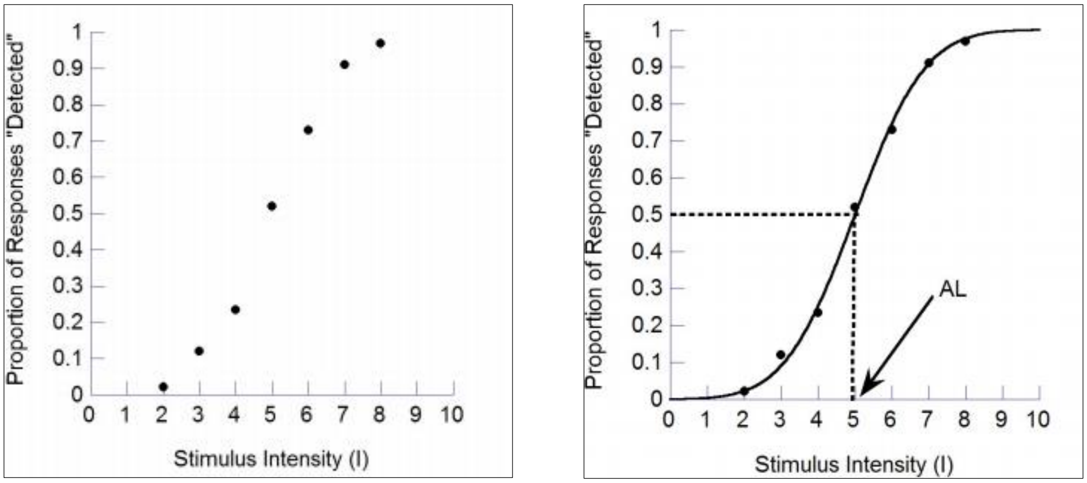


Figure 5.3 Relationship between headways and level of discomfort

5.2.4 Analysis of the Experimental Data

Analysis was carried out to determine the two thresholds indicated in Figure 5.3 based on the driver discomfort thresholds. Threshold 1 delineates 'Very Uncomfortable' headway and 'Somewhat uncomfortable' headway. Threshold 2 delineates 'Somewhat Uncomfortable' and 'No Discomfort' headways. These two thresholds were determined using a modification of the Method of Constant Stimuli (which records the responses detected and plots them as a function of stimulus intensity). Figure 5.4 presents an example of the psychometric graph. When the stimulus intensity is extremely low, the probability of subjects reporting a stimulus detection is close to zero. When the stimulus intensity is high, the experiment participants tend to confirm the detection of stimulus. When the psychometric curves are plotted with an adequate number of measurements, the results often follow a particular “S” shape (or “ogive”), and a theoretical sigmoidal curve could be fitted to the observations.



(a) Datapoints (b) Best-fitting model to the data

Figure 5.4 Concepts of (a) psychometric graph development (b) absolute threshold determination

For this purpose, the cumulative Gaussian distribution is typically used for the curve fitting, and its efficacy in this regard is supported by theory as well as experimental findings in past research. Examples include the outcomes of psychometric studies that are found in biological and psychological science publications (Gescheider, 2013). The maximum likelihood technique can then be used to estimate the parameters (mean and standard variation) that characterize the Gaussian distribution. Figure 5.4(a) presents the observations and Figure 5.4(b) presents a curve drawn to fit these observations.

Using the fitted curve, the threshold is estimated as the stimulus value corresponding to 50% detection as shown in Figure 5.4. The experiment sought to determine the two headway thresholds based on the driver’s comfort levels. Thus, the Method of Constant Stimuli was modified as follows: to measure the headway threshold between ‘No discomfort’ and the ‘Somewhat Uncomfortable’ levels (that is, Threshold 2), all the answers of “Yes” to the first question (Q1) were first placed in the ‘Uncomfortable’ group. Then, the conventional method of constant stimuli method was applied to the ‘No Discomfort’ and ‘Uncomfortable’ classes.

The study followed this process to estimate the first threshold. The fraction of responses for each stimulus level was recorded, and the data were fitted using the cumulative Gaussian function. The distribution mean and standard deviation were estimated using the maximum likelihood method (via a Probit model), and the absolute threshold using the mean value of the distribution was determined.

5.3 Experiment Outcomes

Probit modeling was carried out to determine thresholds and Tables 5.1–5.3 and Figures 5.6–5.7 each present the results (headway measurements) in both manual and AV modes. Thresholds were determined for each of the three groups of drivers: Cautious, Neutral and Confident. Regarding the Confident group of drivers, it was observed that when the distance headway is smaller than the estimated threshold (15.69 m), the drivers tended to take over the automated driving system. In addition, it was observed that the Confident drivers tended to feel uncomfortable with decreases of the distance headway to less than 22.65 m. Regarding the Neutral group of drivers, it was observed that drivers tended to feel uncomfortable when the distance headway was below 40.83 m, and indicated their intention to take over the automated driving system when the distance headway further decreased to levels below 30.39 m. Regarding the Cautious drivers group, it was estimated that Threshold 1 and Threshold 2 are 60m and 37m, respectively.

Table 5.1 Headway measurements – Cautious drivers

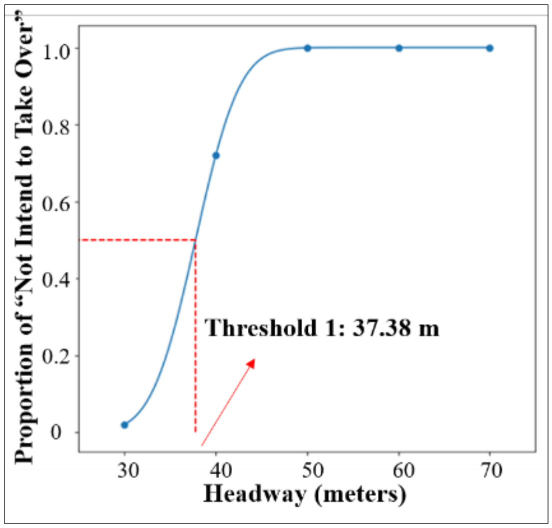
The mean of distance headways in manual mode (m)	66.32				
Stimulus (meters)	30	40	50	60	70
Frequency					
No Discomfort	0	0	7	24	45
Somewhat Uncomfortable	1	36	43	26	5
Very Uncomfortable	49	14	0	0	0
Nr. of Observations	50	50	50	50	50
Threshold 1 in AV mode (meters)	37.38				
Threshold 2 in AV mode (meters)	60.00				

Table 5.2 Headway measurements – Neutral drivers

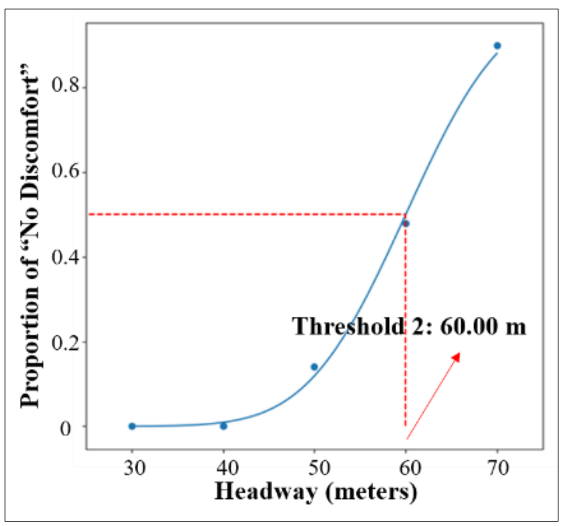
The mean of distance headways in manual mode (m)	42.76				
Stimulus (meters)	15	25	35	45	55
Frequency					
No Discomfort	0	0	5	41	49
Somewhat Uncomfortable	1	1	43	9	0
Very Uncomfortable	0	0	0	0	49
Nr. of Observations	49	49	2	0	1
Threshold 1 in AV mode (meters)	30.39				
Threshold 2 in AV mode (meters)	40.83				

Table 5.3 Headway measurements – Confident drivers

The mean of distance headways in manual mode (m)	23.51				
Stimulus (meters)	13	18	23	28	33
Frequency					
No Discomfort	0	0	29	44	50
Somewhat Uncomfortable	1	48	20	6	0
Very Uncomfortable	49	2	1	0	0
Nr. of Observations	50	50	50	50	50
Threshold 1 in AV mode (meters)	15.69				
Threshold 2 in AV mode (meters)	22.65				

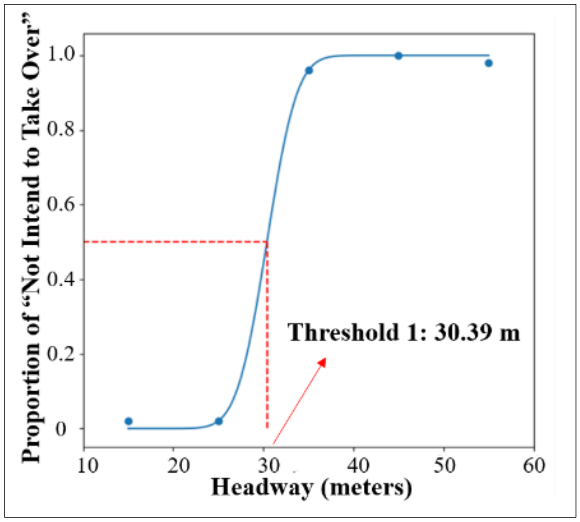


(i) Estimation of Threshold 1

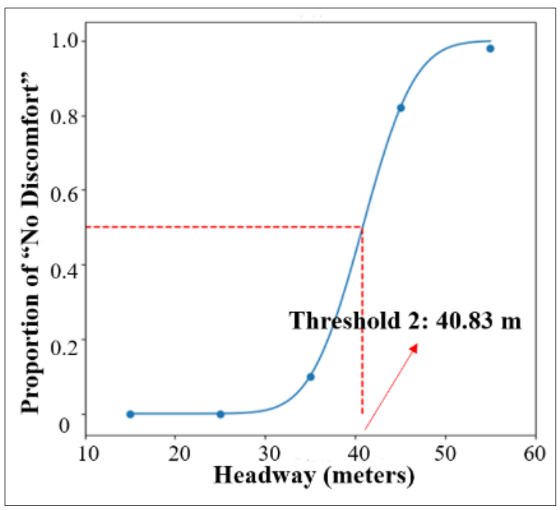


(ii) Estimation of Threshold 2

Figure 5.5 Determination of Headway Thresholds for "Cautious" drivers

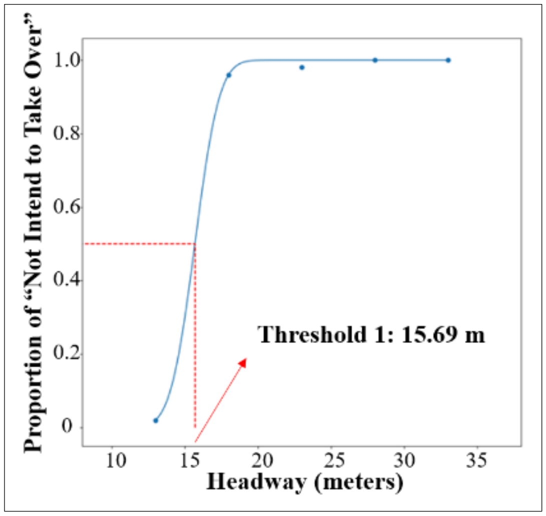


Estimation of Threshold 1

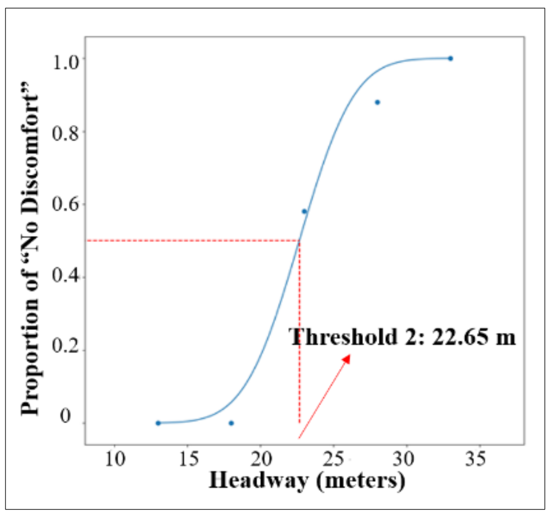


Estimation of Threshold 2

Figure 5.6 Determination of Headway Thresholds for "Neutral" drivers



(i) Estimation of Threshold 1



(ii) Estimation of Threshold 2

Figure 5.7 Determination of Headway Thresholds for "Confident" drivers

CHAPTER 6 CONCLUDING REMARKS

6.1 Summary of Findings and Conclusions

This study investigates the affecting factors that need to be considered to design an in-vehicle situational awareness enhancing system (SAES), which can facilitate AV-manual takeover given partial and conditional automation. The research is divided into two phases. In the first phase, we present a thorough literature review that explores prompt-based SAES for directing drivers' attention to AV-manual takeover and evaluate their impacts on drivers' situational awareness and takeover performance, and we develop SAES inputs and a general SAES that could serve as a starting point for future SAES development.

The second part of the study used driving simulator experiments to demonstrate situational awareness system applications, specifically to investigate drivers' comfortable car-following distances in a CAV environment. The level of comfort was indirectly and implicitly a function of the drivers' situational awareness of the road and traffic environment. The driving simulator had level 3 automation. In the experiment, drivers reported the levels of their discomfort associated with different headways and their intention to take over the vehicle from the automated driving system. This information served as a basis for the threshold headway analysis. Different headway thresholds were determined for three groups of drivers operating at the same vehicle speed. The results suggest that 'Cautious' drivers tend to be more sensitive to headway decreases because they exhibit intentions to take over the driving task from the automated driving system at longer headway relative to confident or neutral drivers. Also, the reference headways (that is, those measured during manual driving) are all slightly longer compared to the automated driving's headway Threshold 2. That is, drivers did not report discomfort even where the CAV maintained headways smaller than those typically adopted by the drivers.

These results could be viewed from the perspective of the role of operator trust in AI technology, and consequently, their intention to take over control of the vehicle from the automated driving. Researchers have shown that the trust in automated driving and the acceptance of technology will influence AV driver/operator's decision to transition between automated and manual modes. Du et al. (2020) inferred that in Level 3 automated driving, certain physiological attributes (which are indicative of the driver's workload and resultant stress) could significantly influence the driver's takeover propensity and performance.

The type of driver could be significant. The current study used a single demographic. However, Chen et al. (2021) showed that older drivers tend to exercise greater caution and thus tend to maintain longer headways. On the other hand, mid-age drivers are more confident of their driving abilities and tend to follow the leading vehicle with smaller headways. On the other hand, novice drivers are more cautious in following a leading vehicle, and keep longer headways (Underwood, 2013). The literature also suggests that irrespective of driver experience and age effects, a cautious style of driving is associated with long headways (Shinar and Schechtman, 2002; Saifuzzaman et al., 2015; Ivanco, 2017; Bao et al., 2020). The current study, consistent with the previous research results which had focused on traditional human-driven operations, suggest that driving styles (measured in terms of caution levels) significantly affects the driver comfort level and hence, their headway lengths, in the context of CAV environment. In particular, the 'Cautious,' 'Neutral,' and 'Confident' drivers tend to deactivate the automated driving mode when the distance headway reach a threshold of 37.38 meters, 30.39 meters, and 15.69 meters, respectively. Interestingly, Martin-Gasulla et al (2019) stated that less cautious car-following behaviors (time headway decrease from 1.8s to 0.6s) of CAVs contribute to a 15% reduction in delay; however, it could be argued that this comes at a cost of decreased safety.

It is anticipated that these insights can help enhance AV user safety and comfort in the prospective future where the traffic stream will be characterized by a mixed stream of HDVs and AVs. The study results can also provide insight into the extent to which reduced headways can improve overall mobility and productivity without jeopardizing AV driver/occupant comfort. Also, the study results suggest that even in the far future of Level 5 automation, human factor issues (specifically, occupant comfort) will continue to be important. From a general perspective, there still exists concern about the levels of comfort and trust that drivers and passengers will have for AI technologies embedded in transportation vehicles. In this vein, the present research presents information that hopefully contributes to increased understanding of headway trade-offs between the mobility (or, travel efficiency) of the vehicle and the driver experience (comfort level) in the context on AV environments.

The findings from this research, hopefully, presents insights that are useful to automated vehicle manufacturers and AV-related technology companies regarding the AV design. It is hoped that due consideration of the results of this study (and indeed, similar research studies), could help in the development of user-friendly AV designs that foster user acceptance and trust of automation (Vob et al., 2018). For example, by learning from the human driver's perception (e.g., different comfortable headways), the car manufacturer is better informed to provide dashboard options that "personalize" the AV to the driving style of a specific driver. However, the results of the current study suggest that capacities and delay values used in highway capacity analysis should be updated using "user-friendly" headways in AV-operations environment. Therefore, in the long run, transportation planning involving autonomous mobility, could be enhanced.

6.2 Study Limitations and Directions for Future Research

The study has a few limitations that could be addressed in future research. First, the levels of driver discomfort could be assessed using objective metrics instead of subjective metrics used in this study. For example, the participants' physiological attributes (using electrocardiogram (ECG) or EEG), could be used to measure their discomfort levels. Second, a driver's assessment of distance headway (and hence, their discomfort level) could be unduly influenced by the volumes and speed of ambient traffic, and the roadway conditions, and therefore, future studies could account for environmental and operational effects on drivers' perception of the existing following headways and therefore, their discomfort levels. Third, a wider and more diverse sample could be used in future research, to better understand how the results vary across the different socio-demographic populations (past studies have observed that trust in automation (and prospectively, headway distances) varies significantly across various population groups). Fourth, past exposure to automation or technology could be affecting drivers' trust in automated driving and subsequently their comfortable level of headways. However, information on the participants past exposure to new automotive technologies was not collected in the current study.

CHAPTER 7 SYNOPSIS OF PERFORMANCE INDICATORS

7.1 USDOT Performance Indicators Part I

Two (2) transportation-related courses were offered annually during the study period that were taught by the PI and teaching assistants (TA) who also served as a research assistant (RA) for this research project. Four graduate students and a post-doctoral researcher (subsequently designated a Visiting Assistant Professor) participated in the research project during the study period. The Visiting Assistant Professor was subsequently appointed as a tenure-track assistant professor at the University of Wisconsin-Madison. Two (2) transportation-related advanced degree programs (MS in Transportation and PhD in Transportation) utilized the CCAT grant funds from this research project, during the study period to support graduate students. This and other CCAT research projects were leveraged to obtain $210,000 in additional funding from the Indiana DOT titled "Integrating Transformative Technologies in Indiana's Transportation Operations". Additional funding worth $100,000 was also provided through a Purdue Graduate Fellowship awarded to one of the students who helped conduct this research.

7.2 USDOT Performance Indicators Part II

Research Performance Indicators: One (1) journal article was produced from this project. Also, through conferences, the research from this project was disseminated to over 92 people from industry, government, and academia. These include: the 2018 Purdue ITE Seminar in West Lafayette, IN; the 2019 International Conference on Smart Cities, Seoul, Korea; and the 2020 Next-generation Transportation Systems Conference, West Lafayette, IN. The study was also presented on Youtube as Episode #10 of CCAT's Research Review Series. The number of views to date is 750.

https://www.youtube.com/watch?v=2rskMX5KN9k

One (1) other related research project was funded by a source other than UTC and matching fund sources. Also, as of the time of writing, there are no new technologies, procedures/policies, and standards/design practices that were produced by this research project.

Leadership Development Performance Indicators

This research project generated 2 academic engagements and 1 industry engagement. The PIs held positions in 2 national organizations that address issues related to this research project.

Education and Workforce Development Performance Indicators

The methods, data and/or results from this study were incorporated in the syllabus for subsequent versions (Fall 2022 and 2023) of the following courses at Purdue University: (a) CE 299: Smart Mobility, an optional undergraduate level course at Purdue' civil engineering B.S. program, and (b) CE 398: Introduction to Civil Engineering Systems, a mandatory undergraduate level course at Purdue University's civil engineering program.

These students will soon be entering the workforce. Thereby, the research helped enlarge the pool of people trained to develop knowledge and utilize at least a part of the technologies developed in this research, and to put them to use when they enter the workforce.

Collaboration Performance Indicators

There was collaboration with other agencies, and 1 agency provided matching funds worth $210,000.

The outputs, outcomes, and impacts are described in Chapter 8.

CHAPTER 8 STUDY OUTCOMES AND OUTPUTS

8.1 Outputs

8.1.1 Publications, conference papers, or presentations

<u>(a) Journal Publications</u>

Li, Y., Chen, T., Chen, S., Labi, S. (2022). Tradeoffs between safe/comfortable headways versus mobility-enhancing headways in an automated driving environment: preliminary insights using a driving simulator experiment, *Frontiers in Engineering & Built Environment*, Volume 1 Issue 2, 173-187, https://doi.org/10.1108/febe-05-2021-0025

<u>(b) Conference Presentations</u>

Li, Y., Peeta, S., Labi, S., (2018). Drivers perception of headways in autonomous vehicle operations. *Road School*, Purdue University, W. Lafayette, IN.

Li, Y., Labi, S. (2019). Drivers' perception of headways in autonomous vehicles, *2019 International Conference on Smart Cities*, Seoul, South Korea.

Li, Y., Chen, S., Labi, S. (2020). A driving simulation experiment to measure headway tradeoffs. in autonomous vehicle operations, *Next-generation Transportation Systems Conference* (online), W. Lafayette, IN.

<u>(c) National Webinar Presentations</u>

Li, Y., Labi, S. (2021). Effect of human drivers' time delay & heterogeneity on traffic stabilization capability of CAVs, August 2021, Presented at the CCAT Research Review Series on Youtube, Episode 10, The Center for Connected and Automated Transportation, Ann Arbor, Michigan. https://www.youtube.com/watch?v=2rskMX5KN9k

8.1.2 Other products

Other products of this research are as follows:

- Material for the Purdue courses "CE 299 (Smart Mobility) and CE 398 (Civil Engineering Systems).
- Research material to support future research related to the subjects of human machine interactions and situational awareness.

8.2 Outcomes

The outcomes of this project are the prospective initiatives or changes that could be made to existing in-vehicle alert warrants and modes, to ensure smooth and safe takeover of the ADS by the driver where necessary. This could lead to regulation, legislation, or policy regarding situational awareness. As this report suggests, precursors to such initiatives could include:

- Increased understanding and awareness of the need for situational awareness in AVs, and that has a profound effect on safety in the emerging era of automated vehicle operations.
- Strong justification to both OEMs to consider installing features in their vehicles that effectively enhance situational awareness.

8.3 Impacts

Automated driving experience and its related tasks including human takeover of the AV, is influenced by various factors including environmental conditions, road and traffic conditions, vehicle sensors, driver attributes, and driver characteristics. This study report discusses the conditions and factors that may prompt a takeover request, different types and modalities of alerts employed in takeover requests, potential non driving related tasks performed by drivers and how each one affects the response time and quality of takeover. In addition, specific physiological and psychological characteristics of the driver affect the driving performance. Such characteristics include driver's trust in the automation, propensity to take over, drivers age, and social demographic factors. These factors can shape autonomous vehicle design and policy and are discussed in this study.

Explorations of risk levels in the driving environment can help vehicle designers, traffic engineers, and policy makers understand the potential risks with autonomous vehicles and consequently institute policy, updated roadway designs, or traffic management plans, to mitigate these risks. Insights regarding takeover alerts and drivers' response to them can help designers understand the most effective ways to alert the drivers of a takeover. Takeover warrants highlight the limitations of the automation and may be instrumental in shaping policy towards AV use.

Understanding passenger attributes and driver characteristics, such as their trust in automation systems, their propensity for or aversion from risk as well as level of aggression in their driving style may aid vehicle designers and engineers to engineer safety-enhancing automation systems to better handle different scenarios. Finally, an understanding of response time can help vehicle designers and manufacturers allocate a sufficient time budget to allow for a successful takeover.

The broader impacts of enhanced situational awareness of AV operators reverberates at various spatial scales of the highway transportation system, from the vehicle itself, to immediate environment where the vehicle operates, to the road (link) section, to the road corridor, and to wider the network in general. At each spatial scale, these impacts include (at least, prospectively) increased traffic flow and throughput, enhanced overall mobility, increased safety and comfort of AV drivers and passengers (particularly, the infirm), and other related accompanying benefits (lower emissions, and social quality due to reduced accidents. The overall project outcomes also include: a broadening of the body of knowledge and technologies associated with human-machine interface and interactions in the context of AVs, enlargement of the pool of people trained to develop knowledge and utilize new technologies and put them to use; improve the physical, institutional, and information resources, such as the CCAT/NEXTRANS Human Factors Research Lab's cab driving simulator (located at Kent Avenue in West Lafayette), that provides students with access to training and new technologies.

REFERENCES

Ackermann, C., Beggiato, M., Schubert, S., & Krems, J. F. (2019). An experimental study to investigate design and assessment criteria: What is important for communication between pedestrians and automated vehicles? Applied Ergonomics, 75, 272–282. https://doi.org/10.1016/j.apergo.2018.11.002

Abuelenin, S.M., Abul-Magd, A.Y. (2015). Effect of minimum headway distance on connectivity of VANETs. AEU-International Journal of Electronics & Communications 69(5), 867-871.

Alrefaie, M. T., Summerskill, S., & Jackon, T. W. (2019). In a heartbeat: Using driver's physiological changes to determine the quality of a takeover in highly automated vehicles, Accident Analysis & Prevention, 131, 180-190.

Andrews, E. C., & Westerman, S. J. (2012). Age differences in simulated driving performance: Compensatory processes, Accident Analysis & Prevention, 45, 660-668.

Bahram, M., Aeberhard, M., Rauch, S., Tanzmeister, G., Thomas, J., Pilat, Y., & Kaempchen, N. (2015). Experience, results and lessons learned from automated driving on Germany's highways, IEEE Intelligent Transportation Systems Magazine, 7(1), 42-57.

Baltodano, S., Sibi, S., Martelaro, N., Gowda, N., & Ju, W. (2015, September). The RRADS platform: a real road autonomous driving simulator. In Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 281-288.

Bao, S., Wu, L., Yu, B., Sayer, J.R. (2020). An examination of teen drivers' car-following behavior under naturalistic driving conditions: With and without an advanced driving assistance system, Accident Analysis & Prevention 147, 105762.

Beller, J., Heesen, M., & Vollrath, M. (2013). Improving the driver–automation interaction: An approach using automation uncertainty, Human Factors, 55(6), 1130-1141.

Boyle, L.N., Lee, J.D. (2010). Using driving simulators to assess driving safety. Accident Analysis & Prevention, 42(3), 785-787.

Brandenburg, S., & Chuang, L. (2019). Takeover requests during highly automated driving: How should they be presented and under what conditions? Transportation Research Part F: Traffic Psychology & Behavior, 66, 214-225.

Brookhuis, K. A., De Waard, D., & Janssen, W. H. (2001). Behavioral impacts of advanced driver assistance systems, European Journal of Transport & Infrastructure Research, 1(3).

Capalar, J., Olaverri-Monreal, C., 2018. Hypovigilance in limited self-driving automation: Peripheral visual stimulus for a balanced level of automation and cognitive workload, in: IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC. 27–31.

Capallera, M., Meteier, Q., De Salis, E., Widmer, M., Angelini, L., Carrino, S., ... & Mugellini, E. (2023). A contextual multimodal system for increasing situation awareness and takeover quality in conditionally automated driving, IEEE Access, 11, 5746-5771.

Carol, L. A. (1992). Desperately seeking SA. TAC Attack (TAC SP 127-1), 32(3), 5-6

Chabris, C., & Simons, D. (2011). The invisible gorilla: How our intuitions deceive us, Harmony.

Charlton, J. L., Oxley, J., Fildes, B., Oxley, P., Newstead, S., Koppel, S., & O'Hare, M. (2006). Characteristics of older drivers who adopt self-regulatory driving behaviors, Transportation Research Part F: Traffic Psychology & Behavior 9(5), 363-373.

Charness, N., Yoon, J. S., Souders, D., Stothart, C., & Yehnert, C. (2018). Predictors of attitudes toward autonomous vehicles: The roles of age, gender, prior knowledge, and personality. Frontiers in Psychology, 9, 2589.

Chen, T., Chen, S., Sze, N.N., Labi, S. (2024). Using safety performance functions, driving simulation experiments, and questionnaire surveys to develop a situational awareness enhancement framework for autonomous vehicle operations, Working Paper, International Consortium for Advanced Transportation Technologies Research (Purdue University, The Hong Kong Polytechnic University, and Korea Advanced Institute of Science and Technology).

Chen, S., Dong, J., Ha, P., Li, Y., Labi, S. (2021). Graph neural network and reinforcement learning for multiagent cooperative control of connected autonomous vehicles. Computer-Aided Civil & Infrastructure Engineering 36(7) 838–857,

Chen, T., Bai, L., Sze, N.N. (2019b). Factors affecting the severity of rear-end conflicts: A driving simulator study. In 2019 5th International Conference on Transportation Information and Safety, 1182-1187. IEEE.

Chen, T., Sze, N. N., Chen, S., Labi, S., & Zeng, Q. (2021b). Analyzing the main and interaction effects of commercial vehicle mix and roadway attributes on crash rates using a Bayesian random-parameter Tobit model. Accident Analysis & Prevention 154, 106089.

Chen, T., Sze, N.N., Bai, L. (2019a). Safety of professional drivers in an ageing society–A driving simulator study. Transportation Res. Part F: Traffic Psychology & Behavior 67 101-112.

Chen, T., Sze, N.N., Newnam, S., Bai, L. (2021a). Effectiveness of the compensatory strategy adopted by older drivers: difference between professional and non-professional drivers. Transportation Research Part F: Traffic Psychology and Behavior 77, 168-180.

Christos Katrakazas, Mohammed Quddus, Wen-Hua Chen; (2019); A new integrated collision risk assessment methodology for autonomous vehicles, Accident Analysis & Prevention, Volume 127, 2019, Pages 61-79, ISSN 0001-4575, https://doi.org/10.1016/j.aap.2019.01.029.

Clark, H., & Feng, J. (2015). Age differences in the takeover of vehicle control and engagement in non-driving-related activities in simulated driving with conditional automation. Accident Analysis & Prevention, 106, 468-479.

Clercq, K., Dietrich, A., Núñez Velasco, J. P., De Winter, J., & Happee, R. (2019). External human-machine interfaces on automated vehicles: Effects on pedestrian crossing decisions. Human Factors, 61(8), 1353-1370.

Cohen-Lazry, G., Katzman, N., Borowsky, A., & Oron-Gilad, T. (2019). Directional tactile alerts for takeover requests in highly automated driving. Transportation Research Part F: Traffic Psychology & Behavior, 65, 217-226.

Cord, A., & Gimonet, N. (2014). Detecting unfocused raindrops: In-vehicle multipurpose cameras. IEEE Robotics & Automation Magazine, 21(1), 49-56.

Cutting, J.E., Vishton, P.M. (1995). Perceiving layout and knowing distances: The integration, relative potency, and contextual use of different information about depth, Perception of Space and Motion, 69-117, Academic Press.

Darbha, S., Konduri, S., Pagilla, P.R. (2018). Benefits of V2V communication for autonomous and connected vehicles. IEEE Transactions on Intelligent Transportation Systems 20(5), 1954-1963.

Deb, S., Rahman, M. M., Strawderman, L. J., & Garrison, T. M. (2018). Pedestrians' receptivity toward fully automated vehicles: Research review and roadmap for future research. IEEE Transactions on Human-Machine Systems, 48(3), 279-290.

Deo, N., Trivedi, M.M. (2019). Looking at the driver/rider in autonomous vehicles to predict takeover readiness. IEEE Transactions on Intelligent Vehicles 5(1), 41-52.

Dixit, V. V., Chand, S., & Nair, D. J. (2016). Autonomous vehicles: disengagements, accidents, and reaction times. PLoS one, 11(12), e0168054.

Dominguez, C. (1994). Can SA be defined? In Situation Awareness: Papers and Annotated Bibliography (U). Armstrong Laboratory, Wright-Patterson AFB: OH.

Dong, J., Chen, S., Li, Y., Du, R., Steinfeld, A., Labi, S. (2020a). Space-weighted information fusion using deep reinforcement learning: The context of tactical control of lane-changing autonomous vehicles and connectivity range assessment. Transportation Research Part C: Emerging Technologies 128, 103192, https://doi.org/10.1016/j.trc.2021.103192

Drew, T., Võ, M. L. H., & Wolfe, J. M. (2013). The invisible gorilla strikes again: Sustained inattentional blindness in expert observers. Psychological Science, 24(9), 1848-1853.

Du, R., Chen, S., Li, Y., Dong, J., Ha, P., Labi, S. (2020). A cooperative control framework for CAV lane change in a mixed traffic environment. arXiv preprint arXiv:2010.05439.

Duan, J., Li, Z., Salvendy, G. (2013). Risk illusions in car following: Is a smaller headway always perceived as more dangerous? Safety Science 53, 25-33.

Elbanhawi, M., Simic, M., & Jazar, R. (2015). In the passenger seat: investigating ride comfort measures in autonomous cars. IEEE Intelligent transportation systems magazine, 7(3), 4-17.

Endsley, M. R. (1988). Situation awareness global assessment technique (SAGAT). Proceedings of the IEEE 1988 national aerospace and electronics conference, Dayton, OH.

Endsley, M. R. (1995). Measurement of situation awareness in dynamic systems. Human Factors, 37(1), 65-84.

ETSI (2011), Intelligent Transport Systems (ITS); Decentralized Congestion Control Mechanisms for Intelligent Transport Systems Operating in the 5 GHz Range; Access Layer Part, TS 102 687 V1.1.1, European Telecommunications Standards Institute.

Faltaous, S., Baumann, M., Schneegass, S., & Chuang, L. L. (2018). Design guidelines for reliability communication in autonomous vehicles Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Toronto, Canada.

Favarò, F. M. (2021). Impact of smart phones' interaction modality on driving performance for conventional and autonomous vehicles, Mineta Transportation Institute Publications. https://doi.org/10.31979/mti.2020.1813

Favarò, F. M., Eurich, S. O., & Rizvi, S. S. (2019). Human problems in semi-autonomous vehicles: Understanding drivers' reactions to off-nominal scenarios, International Journal of Human–Computer Interaction, 35(11), 956-971.

Fisher, D.L., Rizzo, M., Caird, J.K., Lee, J.D. (2011), Handbook of driving simulation for engineering, medicine, and psychology, Handbook of Driving Simulation for Engineering, Medicine, and Psychology, https://doi.org/10.1201/b10836-2

Fleskes, K., & Hurwitz, D. S. (2019). Influence of bicyclist presence on driver performance during automated vehicle takeover requests. Transportation Research Part F: Traffic Psychology & Behavior, 64, 495-508.

Forster, Y., Naujoks, F., Neukum, A., & Huestegge, L. (2017). Driver compliance to takeover requests with different auditory outputs in conditional automation. Accident Analysis & Prevention 109, 18-28, doi: 10.1016/j.aap.2017.09.019

Fuller, R. G. (1981). Determinants of time headway adopted by truck drivers. Ergonomics 24(6), 463-474.

Gang, N., Sibi, S., Michon, R., Mok, B., Chafe, C., & Ju, W. (2018, September). Don't be alarmed: Sonifying autonomous vehicle perception to increase situation awareness. In Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 237-246.

Gescheider, G.A. (1985), Psychophysics: Method, Theory, and Application, Psychology Press.

Ghasemzadeh, A., & Ahmed, M. M. (2018). Utilizing naturalistic driving data for in-depth analysis of driver lane-keeping behavior in rain: Non-parametric MARS and parametric logistic regression modeling approaches. Transportation Research Part C: Emerging Technologies, 90, 379-392.

GHSA. (2018). Preparing for Automated Vehicles: Traffic Safety Issues for States. Governors Highway Safety Association, Washington, DC. Retrieved from https://www.ghsa.org/sites/default/files/2018-08/Final_AVs2018.pdf%0Ahttps://trid.trb.org/view/1532106

Gold, C., Damböck, D., Lorenz, L., & Bengler, K. (2013, September). "Takeover!" How long does it take to get the driver back into the loop?. In Proceedings of the human factors and ergonomics society annual meeting, Vol. 57, No. 1, 1938-1942, Sage Publications, Los Angeles, CA.

Gold, C., Happee, R., & Bengler, K. (2018). Modeling takeover performance in level 3 conditionally automated vehicles. Accident Analysis & Prevention, 116, 3-13.

Gold, C., Happee, R., Bengler, K. (2018). Modeling takeover performance in level 3 conditionally automated vehicles. Accid. Anal. Prev. 116, 3–13. https://doi.org/10.1016/j.aap.2017.11.009

Gold, C., Kerber, M., Hohenberger, C., Lechner, D., & Bengler, K. (2015). Trust in automation Ð Before and after the experience of takeover scenarios in a highly automated vehicle. In Procedia Manufacturing 6th International Conference on Applied Human Factors and Ergonomics (AHFE) and the Affiliated Conferences (Vol. 3, pp. 3025Ð3032). Elsevier B.V. https://doi.org/10.1016/j.promfg.2015.07.847

Gruenefeld, U., Weiß, S., Löcken, A., Virgilio, I., Kun, A. L., & Boll, S. (2019, September). VRoad: gesture-based interaction between pedestrians and automated vehicles in virtual reality. In Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications: Adjunct Proceedings, 399-404.

Ha, P., Chen, S., Du, R., Dong, J., Li, Y., Labi, S. (2020). Vehicle connectivity and automation: a sibling relationship, Frontiers in Built Environment 6, 590036. https://doi.org/10.3389/fbuil.2020.590036

Haines, R. F., and Flateau, C. (1992). Night Flying. Blue Ridge Summit, PA: TAB Books.

Hamilton, W. L. (1987). Situation Awareness Metrics Program, SAE Tech. Paper Series 871767.

Hanley, S. (2019). Nissan ProPilot 2.0 is a lot like Tesla Autopilot, with one key difference, CleanTechnica, https://cleantechnica.com/2019/05/26/nissan-propilot-2-0-is-a-lot-like-tesla-autopilot-with-one-key-difference/

Happee, R., Gold, C., Radlmayr, J., Hergeth, S., & Bengler, K. (2017). Takeover performance in evasive maneuvers. Accident Analysis & Prevention, 106, 211-222.

Harding, J., Powell, G., Yoon, R., Fikentscher, J., Doyle, C., Sade, D., ... & Wang, J. (2014). Vehicle-to-vehicle communications: readiness of V2V technology for application (No. DOT HS 812 014), National Highway Traffic Safety Administration, Washington, DC.

Hartman, B. O., and Secrist, G. E. (1991). Situational awareness is more than exceptional vision. Aviation, Space, and Environmental Medicine, 62, 1084-108

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. Technological Forecasting & Social Change 105, 105-120.

Hergeth, S., Lorenz, L., & Krems, J. F. (2017). Prior familiarization with takeover requests affects drivers' takeover performance and automation trust. Human Factors, 59(3), 457-470.

Hester, M., Lee, K., & Dyre, B. P. (2017a). Driver takeover: A preliminary exploration of driver trust and performance in autonomous vehicles. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol. 61, No. 1, 1969-1973. Sage CA: Los Angeles, CA: SAGE Publications.

Hester, T., Vecerik, M., Scholz, J., Wang, F., Pietquin, O., Piot, B., ... & Riedmiller, M. (2017b). Leveraging demonstrations for deep reinforcement learning on robotics problems with sparse rewards. arXiv preprint arXiv:1707.08817.

Ho, G., Wheatley, D., & Scialfa, C. T. (2005). Age differences in trust and reliance of a medication management system. Interacting with Computers, 17(6), 690-710.

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. Human Factors, 57(3), 407-434.

Huang, G., Steele, C., Zhang, X., & Pitts, B. J. (2019). Multimodal cue combinations: a possible approach to designing in-vehicle takeover requests for semi-autonomous driving. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting 2019, November (Vol. 63, No. 1, pp. 1739-1743). Sage CA: Los Angeles, CA: SAGE Publications.

Ivanco, A. (2017). Fleet analysis of headway distance for autonomous driving. Journal of Safety Research 63, 145-148.

Kim, j., Kim, H. S., Kim, W., & Yoon, D. (2018). Takeover performance analysis depending on the drivers' non-driving secondary tasks in automated vehicles. In 2018 International Conference on Information and Communication Technology Convergence (ICTC), 1364-1366. IEEE.

Jung, C., Lee, D., Lee, S., Shim, D.H. (2020). V2X-Communication-aided autonomous driving: system design and experimental validation. Sensors, 20(10), 2903.

Karjanto, J., Yusof, N., Terken, J. M. B., Delbressine, F. L. M., Hassan, M. Z. B., & Rauterberg, G. W. M. (2017). Simulating autonomous driving styles: Accelerations for three road profiles. In MATEC web of conferences (Vol. 90, 1-16). EDP Sciences.

Kenney, J. B. (2011). Dedicated short-range communications (DSRC) standards in the United States. Proceedings of the IEEE, 99(7), 1162-1182.

Kerschbaum, P., Lorenz, L., Hergeth, S., & Bengler, K. (2015, June). Designing the human-machine interface for highly automated cars—Challenges, exemplary concepts, and studies. In 2015 IEEE International Workshop on Advanced Robotics and its Social Impacts (ARSO), 1-6. IEEE.

Kim, H. J., & Yang, J. H. (2017). Takeover requests in simulated partially autonomous vehicles considering human factors. IEEE Transactions on Human-Machine Systems, 47(5), 735-740.

Kim, J. W., & Yang, J. H. (2020). Understanding metrics of vehicle control takeover requests in simulated automated vehicles, International journal of automotive technology, 21, 757-770.
Kim, M. K., Park, J. H., Oh, J., Lee, W. S., & Chung, D. (2019). Identifying and prioritizing the benefits and concerns of connected and autonomous vehicles: A comparison of individual and expert perceptions, Research in Transportation Business & Management, 32, 100438.
Kim, N., Jeong, K., Yang, M., Oh, Y., & Kim, J. (2017). Are You Ready to Takeover?: An Exploratory Study on Visual Assistance to Enhance Driver Vigilance, In Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems (pp. 1771-1778). ACM. doi: 10.1145/3027063.3053155
Kim, Y., Guanetti, J., & Borrelli, F. (2018). Control of connected and automated vehicles: State of the art and future challenges, Annual Reviews in Control, 45, 18-40.
Köhn, T., Gottlieb, M., Schermann, M., & Krcmar, H. (2019, March). Improving takeover quality in automated driving by interrupting non-driving tasks. In Proceedings of the 24th International Conference on Intelligent User Interfaces (pp. 510-517).
Körber, M., Baseler, E., & Bengler, K. (2018). Introduction matters: Manipulating trust in automation and reliance in automated driving. Applied Ergonomics, 66, 18-31.
Körber, M., Gold, C., Lechner, D., & Bengler, K. (2016). The influence of age on the takeover of vehicle control in highly automated driving. Transportation Research Part F: Traffic Psychology & Behavior, 39, 19-32.
Körber, M., Gold, C., Lechner, D., & Bengler, K. (2017). The influence of age on the takeover of vehicle control in highly automated driving. Transportation Research Part F: Traffic Psychology and Behavior, 39, 19-32.
Krok, A. (2016). Chicago City Council might ban autonomous cars. CNET. Retrieved from https://www.cnet.com/roadshow/news/chicago-city-council-might-ban-autonomous-cars/
Kunze, A., Summerskill, S. J., Marshall, R., & Filtness, A. J. (2019). Conveying uncertainties using peripheral awareness displays in the context of automated driving. Proceedings - 11th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications, AutomotiveUI 2019. https://doi.org/10.1145/3342197.3344537
Kyriakidis, M., de Winter, J. C., Stanton, N., Bellet, T., van Arem, B., Brookhuis, K., ... & Happee, R. (2019). A human factors perspective on automated driving. Theoretical Issues in Ergonomics Science, 20(3), 223-249.
Labi, S. (2014). Civil engineering systems, Wiley, Hoboken, NJ.
Labi, S. (2023). The safety bump during the AV transition period. Working Paper, Transportation and Infrastructure Systems Division, Lyles School of Civil Engineering, Purdue University, W. Lafayette, IN.
Large, D.R., Burnett, G., Morris, A., Muthumani, A., Matthias, R. (2018). A longitudinal simulator study to explore drivers' behavior during highly-automated driving, in: Advances in Intelligent Systems & Computing, 583–594. https://doi.org/10.1007/978-3-319-60441-1_57
Lee, K. M. (2004). Presence, explicated. Communication theory, 14(1), 27-50.
Lewis-Evans, B., De Waard, D., Brookhuis, K.A. (2010). That's close enough—A threshold effect of time headway on the experience of risk, task difficulty, effort, and comfort. Accident Analysis & Prevention, 42(6), 1926-1933.
Li, S., Blythe, P., Guo, W., & Namdeo, A. (2019). Investigating the effects of age and disengagement in driving on driver's takeover control performance in highly automated vehicles. Transportation Planning and Technology, 42(5), 470-497.

Li, Y., Chen, T., Chen, S. and Labi, S. (2021), Tradeoffs between safe/comfortable headways versus mobility-enhancing headways in an automated driving environment: preliminary insights using a driving simulator experiment, Frontiers in Engineering & Built Environment, 1(2), 173-187. https://doi.org/10.1108/FEBE-05-2021-0025

Lindemann, P., Lee, T. Y., & Rigoll, G. (2018). Catch my drift: Elevating situation awareness for highly automated driving with an explanatory windshield display user interface. Multimodal Technologies and Interaction, 2(4), 71.

Litman, T. (2014) Autonomous Vehicle Implementation Predictions: Implications for Transport Planning, Victoria Transport Policy Institute

Löcken, A., Heuten, W., & Boll, S. (2016). Autoambicar: Using ambient light to inform drivers about intentions of their automated cars. AutomotiveUI 2016 - 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Adjunct Proceedings. https://doi.org/10.1145/3004323.3004329

Lorenz, L., Radlmayr, J., Gold, C., Farid, M., & Bengler, K. (2014, September). How traffic situations and non-driving related tasks affect the takeover quality in highly automated driving. In Proceedings of the human factors and ergonomics society annual meeting (Vol. 58, No. 1, pp. 2063-2067). Sage CA: Los Angeles, CA: Sage Publications.

Lotz, A., Russwinkel, N., & Wohlfarth, E. (2019). Response times and gaze behavior of truck drivers in time critical conditional automated driving takeovers. Transportation research part F: Traffic Psychology & Behavior, 64, 532-551.

Ma, R., & Kaber, D. B. (2007). Situation awareness and driving performance in a simulated navigation task. Ergonomics, 50(8), 1351-1364.

Makishita, H., & Matsunaga, K. (2008). Differences of drivers' reaction times according to age and mental workload. Accident Analysis & Prevention, 40(2), 567-575.

Marsh, S., & Dibben, M. R. (2003). The role of trust in information science and technology. Annual Review of Information Science and Technology (ARIST), 37, 465-98.

Martchouk, M., Mannering, F., Bullock, D. (2010). Analysis of freeway travel time variability using Bluetooth detection. Journal of Transportation Engineering 137(10), 697-704.

Martelaro, N., Sirkin, D., Ju, W. (2015). Daze: A real-time situation awareness measurement tool for driving. In Proc. of the ACM/IEEE Intl. Conf. on Automotive User Interfaces and Interactive Vehicular Interactions. ACM, 158–163

Martin-Gasulla, M., Sukennik, P., Lohmiller, J. (2019). Investigation of the impact on throughput of connected autonomous vehicles with headway based on the leading vehicle type, Transportation Research Record, 2673(5), 617-626.

McLeod, S., Curtis, C., Hultén, J., Pettersson-Lofstedt, F., Paulsson, A., & Hedegaard Sørensen, C. (2021). Knowledge for policy-making in times of uncertainty: the case of autonomous vehicle model results. Transport Reviews, 41(4), 478-498.

Merat, N., Jamson, A. H., Lai, F. C., Daly, M., & Carsten, O. M. (2014). Transition to manual: Driver behaviour when resuming control from a highly automated vehicle. Transportation Research Part F: Traffic Psychology & Behavior, 27, 274-282.

Miller, D., Johns, M., Mok, B., Gowda, N., Sirkin, D., Lee, K., Ju, W. (2016). Behavioral measurement of trust in automation: the trust fall, Procs., Human Factors and Ergonomics Society Annual Meeting 60(1), 1849-1853, SAGE Publications, Los Angeles, CA.

Mok, B. K. J., Johns, M., Lee, K. J., Ive, H. P., Miller, D., & Ju, W. (2015). Timing of unstructured transitions of control in automated driving. In 2015 IEEE Intelligent Vehicles Symposium (IV) (pp. 1167-1172). IEEE.

Mok, B., Johns, M., Yang, S., & Ju, W. (2017). Reinventing the wheel: Transforming steering wheel systems for autonomous vehicles. UIST 2017 - Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology. https://doi.org/10.1145/3126594.3126655

Molnar, L.J., Ryan, L.H., Pradhan, A.K., Eby, D.W., Louis, R.M., Zakrajsek, J.S. (2018). Understanding trust and acceptance of automated vehicles: An exploratory simulator study of transfer of control between automated and manual driving. Transportation Research Part F: Traffic Psychology & Behavior 58, 319-328.

National Highway Traffic Safety Administration Database, 2016

Naujoks, F., Purucker, C., Neukum, A., Wolter, S., & Steiger, R. (2015). Controllability of partially automated driving functions–does it matter whether drivers are allowed to take their hands off the steering wheel? Transportation Research Part F: Traffic Psychology & Behavior, 35, 185-198.

Nees, M. A. (2016, September). Acceptance of self-driving cars: An examination of idealized versus realistic portrayals with a self-driving car acceptance scale, In Proceedings of the human factors and ergonomics society annual meeting (Vol. 60, No. 1, pp. 1449-1453). Sage CA: Los Angeles, CA: SAGE Publications.

NHTSA (2013). Preliminary Statement of Policy Concerning Automated Vehicles. National Highway Traffic Safety Administration Washington, DC. https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/automated_vehicles_policy.pdf

Ni, R., Kang, J.J., Andersen, G.J. (2010). Age-related declines in car-following performance under simulated fog conditions, Accident Analysis & Prevention, 42(3), 818-826.

Oliver, J. G. (1990). Improving situational awareness through use of intuitive pictorial displays (SAE Technical Paper Series, No. 901829). Warrendale, PA: SAE.

Payre, W., Cestac, J., & Delhomme, P. (2016). Fully automated driving: Impact of trust and practice on manual control recovery, Human Factors 58(2), 229-241.

Petermeijer, S., Bazilinskyy, P., Bengler, K., & De Winter, J. (2017). Takeover again: Investigating multimodal and directional TORs to get the driver back into the loop, Applied Ergonomics, 62, 204-215.

Petersen, L., Robert, L., Yang, J., Tilbury, D. (2019). Situational awareness, driver's trust in automated driving systems and secondary task performance, SAE International Journal of Connected and Autonomous Vehicles, SAE.

Piccinini, G. F. B., Rodrigues, C. M., Leitão, M., & Simões, A. (2014). Driver's behavioral adaptation to Adaptive Cruise Control (ACC): The case of speed and time headway, Journal of Safety Research 49, 77-84.

Pokam, R., Debernard, S., Chauvin, C., & Langlois, S. (2019). Principles of transparency for autonomous vehicles: first results of an experiment with an augmented reality human–machine interface, Cognition, Technology & Work, 21, 643-656.

Pourgholamali, M., Miralinaghi, M., Seilabi, S. E., & Labi, S. (2023). Sustainable deployment of autonomous vehicles dedicated lanes in urban traffic networks, Sustainable Cities and Society, 99, 104969.

Pradhan, A.K., Crossman, J., Sypniewski, A., 2019. Improving driver engagement during l2 automation: a pilot study, in: Proceedings of the Tenth International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design, 280–286.

Radlmayr, J., Gold, C., Lorenz, L., Farid, M., & Bengler, K. (2014, September). How traffic situations and non-driving related tasks affect the takeover quality in highly automated driving. In Proceedings of the human factors and ergonomics society annual meeting (Vol. 58, No. 1, pp. 2063-2067), Sage CA: Los Angeles, CA: Sage Publications.

Rasouli, A., & Tsotsos, J. K. (2018). Joint attention in driver-pedestrian interaction: from theory to practice. arXiv preprint arXiv:1802.02522.

Rasshofer, R. H., Spies, M., & Spies, H. (2011). Influences of weather phenomena on automotive laser radar systems, Advances in Radio Science, 9, 49-60.

Razmi, Rad, de Almeida Correia, G. H., & Hagenzieker, M. (2020). Pedestrians' road crossing behavior in front of automated vehicles: Results from a pedestrian simulation experiment using agent-based modelling, Transportation Research Part F: Traffic Psychology and Behavior, 69, 101-119.

Revell, K., Keszthelyi, D., & Stanton, J. B. N. Taking control without guidance: What do drivers of semi-autonomous vehicles think about? Contemporary Ergonomics and Human Factors 2019. Eds. Rebecca Charles and David Golightly. CIEHF.

Risto, M., & Martens, M. H. (2013). Time and space: The difference between following time headway and distance headway instructions. Transportation Research Part F: Traffic Psychology and Behavior, 17, 45-51.

Risto, M., Martens, M.H. (2013). Time and space: The difference between following time headway and distance headway instructions. Transportation Research Part F: Traffic Psychology and Behavior 17, 45-51.

Robertson, R. D., Meister, S. R., Vanlaar, W. G., & Hing, M. M. (2017). Automated vehicles and behavioral adaptation in Canada. Transp. Research Part A: Policy& Practice, 104, 50-57.

Rodríguez Palmeiro, A., van der Kint, S., Vissers, L., Farah, H., de Winter, J. C., & Hagenzieker, M. (2018). Interaction between pedestrians and automated vehicles: A Wizard of Oz experiment. Transportation Research Part F: Trac Psychology and Behavior, 58, 1005–1020. https ://doi.org/10.1016/j.trf.2018.07.020

Sadeghian Borojeni, S., Boll, S. C., Heuten, W., Bülthoff, H. H., & Chuang, L. (2018, April). Feel the movement: Real motion influences responses to takeover requests in highly automated vehicles. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (pp. 1-13).

SAE International. (2021), Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles J3016_202104, SAE International.

SAE (2014). J3016_201401, Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems. Retrieved from: https://www.sae.org/standards/content/j3016_201401/

SAE (2016). J3016_201609, Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems. Retrieved from: https://www.sae.org/standards/content/j3016_201609/

Saeed, A. S., Younes, A. B., Cai, C., & Cai, G. (2018). A survey of hybrid unmanned aerial vehicles, Progress in Aerospace Sciences, 98, 91-105.

Saifuzzaman, M., Haque, M.M., Zheng, Z., Washington, S. (2015). Impact of mobile phone use on car-following behaviour of young drivers. Accident Analysis & Prevention, 82, 10-19.

Salmon, P., Stanton, N., Walker, G., & Green, D. (2006). Situation awareness measurement: A review of applicability for C4i environments, Applied Ergonomics, 37(2), 225-238.

Scerbo, M.W., Mouloua, M.E. (Eds.), 1999. Automation technology and human performance: Current research and trends, Conference on Automation Technology and Human Performance, Lawrence Erlbaum Associates Publishers.

Schmidt, G. J., & Rittger, L. (2017). Guiding driver visual attention with LEDs, AutomotiveUI 2017 - 9th International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications, Proceedings. https://doi.org/10.1145/3122986.3122994

Schömig, N., Hargutt, V., Neukum, A., Petermann-Stock, I., & Othersen, I. (2015). The interaction between highly automated driving and the development of drowsiness, Procedia Manufacturing, 3, 6652-6659.

Schroeter, R., Steinberger, F., 2016. Pokémon DRIVE: Towards increased situational awareness in semi-automated driving, Proc. 28th Aust. Conf. Comput. Interact. 25–29. https://doi.org/10.1145/3010915.3010973

Shinar, D., Schechtman, E. (2002). Headway feedback improves intervehicular distance: A field study, Human Factors 44(3), 474-481.

Shinar, D., Tractinsky, N., Compton, R. (2005). Effects of practice, age, and task demands, on interference from a phone task while driving, Accident Analysis & Prevention 37(2), 315-326.

Siebert, F. W., Oehl, M., & Pfister, H. R. (2014). The influence of time headway on subjective driver states in adaptive cruise control, Transportation Research Part F: Traffic Psychology and Behavior, 25, 65-73.

Siebert, F.W., Oehl, M., Pfister, H.R. (2014). The influence of time headway on subjective driver states in adaptive cruise control, Transportation Research Part F: Traffic Psychology and Behavior 25, 65-73.

Sirkin, D., Martelaro, N., Johns. M., Ju, W. (2017). Toward measurement of situation awareness in autonomous vehicles, CHI Conference on Human Factors in Computing Systems (CHI-2017), Denver, CO, May 6-11, 2017, http://dx.doi.org/10.1145/3025453.3025822

Smith, K., & Hancock, P. A. (1995). Situation awareness is adaptive, externally directed consciousness, Human Factors, 37(1), 137-148.

Sonoda, K., & Wada, T. (2017). Displaying System Situation Awareness Increases Driver Trust in Automated Driving. IEEE Transactions on Intelligent Vehicles, 2(3). https://doi.org/10.1109/TIV.2017.2749178

Stanton, N.A., and Edworthy, J. (1999). Human factors in auditory warnings, Ashgate, 1999.

Stanton, N.A., and Marsden, P. (1996). From fly-by-wire to drive-by-wire: safety implications of automation in vehicles, Safety Science 24, No. 1, 35-49

Stockert, S., Richardson, N. T., & Lienkamp, M. (2015). Driving in an Increasingly Automated World – Approaches to Improve the Driver-automation Interaction, Procedia Manufacturing, 3. https://doi.org/10.1016/j.promfg.2015.07.797

Suzuki, H., Nakatsuji, T. (2015), Dynamic estimation of headway distance in vehicle platoon system under unexpected car-following situations, Transportation Research Procedia, Volume 6, 2015, Pages 172-188 https://doi.org/10.1016/j.trpro.2015.03.014.

Taieb-Maimon, M., Shinar, D. (2001), Minimum and comfortable driving headways: Reality versus perception, Human Factors, https://doi.org/10.1518/001872001775992543.

Tanshi, F., & Söffker, D. (2019, June). Modeling of takeover variables with respect to driver situation awareness and workload for intelligent driver assistance, In 2019 IEEE Intelligent Vehicles Symposium (IV) (pp. 1667-1672). IEEE.

Taylor, R. M. (1990). Situation awareness rating technique (SART): the development of a tool for aircrew systems design. In Situational Awareness in Aerospace Operations (Chapter 3). France: Neuilly sur-Seine, NATO-AGARD-CP

Telpaz, A., Rhindress, B., Zelman, I., & Tsimhoni, O. (2015, September). Haptic seat for automated driving: Preparing the driver to take control effectively. In Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications.

Tenney, Y. J., Adams, M. J., Pew, R. W., Huggins, A. W., and Rogers, W. H. (1992). A principled approach to the measurement of situation awareness in commercial aviation, NASA Contractor Report 4451, Langley Research Center: NASA.

The Guardian. (2016), Tesla driver dies in first fatal crash while using autopilot mode. Retrieved from:www.theguardian.com/technology/2016/jun/30/tesla-autopilot-death-self-driving-car-elon-musk

Tijerina, L., Blommer, M., Curry, R., Swaminathan, R., Kochhar, D. S., & Talamonti, W. (2016). An exploratory study of driver response to reduced system confidence notifications in automated driving, IEEE Transactions on Intelligent Vehicles, 1(4), 325-334.

Tremblay, Durso, F.T., & Dattel, A.R. (2004). SPAM: The real-time assessment of SA, In S. Banbury & S. Tremblay (Eds.), A cognitive Approach to Situation Awareness: Theory and Application (1st Ed.). Great Britain: Ashgate Publishing.

Ulahannan, A., Jennings, P., Oliveira, L., & Birrell, S. (2020). Designing an adaptive interface: Using eye tracking to classify how information usage changes over time in partially automated vehicles, IEEE Access, 8, 16865-16875.

Underwood, G. (2013). On-road behavior of younger and older novices during the first six months of driving, Accident Analysis & Prevention, 58, 235-243.

Van Den Beukel, A. P., & Van Der Voort, M. C. (2013, October). The influence of time-criticality on situation awareness when retrieving human control after automated driving, In 16th International IEEE Conference on Intelligent Transportation Systems, 2000-2005, IEEE.

van der Heiden, R. M., Iqbal, S. T., & Janssen, C. P. (2017, May). Priming drivers before handover in semi-autonomous cars, In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, 392-404).

Velasco, J. P. N., Farah, H., van Arem, B., & Hagenzieker, M. P. (2019). Studying pedestrians' crossing behavior when interacting with automated vehicles using virtual reality, Transportation Research Part F: Traffic Psychology and Behavior, 66, 1-14.

Vob, G.M., Keck, C.M., Schwalm, M. (2018). Investigation of drivers' thresholds of a subjectively accepted driving performance with a focus on automated driving, Transportation Research Part F: Traffic Psychology and Behaviour, 56, 280-292.

Vogel, K. (2003). A comparison of headway and time to collision as safety indicators, Accident Analysis & Prevention, 35(3), 427-433.

Vogelpohl, T., Kühn, M., Hummel, T., & Vollrath, M. (2019). Asleep at the automated wheel- Sleepiness and fatigue during highly automated driving, Accident Analysis & Prevention, 126, 70-84.

Wandtner, B., Schömig, N., & Schmidt, G. (2018). Effects of non-driving related task modalities on takeover performance in highly automated driving, Human factors, 60(6), 870-881.

Wang, S., Jiang, Z., Noland, R. B., & Mondschein, A. S. (2020). Attitudes towards privately-owned and shared autonomous vehicles, Transportation Research Part F: Traffic Psychology and Behavior, 72, 297-306.

Weinbeer, V., Muhr, T., Bengler, K., Baur, C., Radlmayr, J., & Bill, J. (2017). Highly automated driving: How to get the driver drowsy and how does drowsiness influence various takeover-aspects? In 8. Tagung Fahrerassistenz.

Wiedemann, K., Naujoks, F., Wörle, J., Kenntner-Mabiala, R., Kaussner, Y., & Neukum, A. (2018). Effect of different alcohol levels on takeover performance in conditionally automated driving, Accident Analysis & Prevention, 115, 89-97.

Wiegand, G., Mai, C., Liu, Y., & Hubmann, H. (2018). Early takeover preparation in stereoscopic 3D, In Adjunct proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 142-146.

Winsum, W.V., Heino, A. (1996). Choice of time-headway in car-following and the role of time-to-collision information in braking, Ergonomics, 39(4), 579-592.

Wright, T. J., Agrawal, R., Samuel, S., Wang, Y., Zilberstein, S., & Fisher, D.L. (2018). Effective cues for accelerating young drivers' time to transfer control following a period of conditional automation, Accident Analysis & Prevention, 116, 14-20.

Wu, B., Wan, A., Yue, X., & Keutzer, K. (2018, May). Squeezeseg: Convolutional neural nets with recurrent CRF for real-time road-object segmentation from 3d lidar point cloud. In 2018 IEEE international conference on robotics and automation (ICRA) (pp. 1887-1893). IEEE.

Wu, S. S. (2020). Autonomous vehicles, trolley problems, and the law. Ethics & Information Technology, 22(1), 1-13.

Wulf, F., Rimini-Döring, M., Arnon, M., & Gauterin, F. (2014). Recommendations supporting situation awareness in partially automated driver assistance systems, IEEE Transactions on Intelligent Transportation Systems, 16(4), 2290-2296.

Wulf, F., Zeeb, K., Rimini-Döring, M., Arnon, M., & Gauterin, F. (2013, October). Effects of human-machine interaction mechanisms on situation awareness in partly automated driving. In 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013), 2012-2019, IEEE.

Yoon, S. H., Kim, Y. W., & Ji, Y. G. (2019). The effects of takeover request modalities on highly automated car control transitions, Accident Analysis & Prevention, 123, 150-158.

Yoshida, H., Hyakudome, T., Ishibashi, S., Sawa, T., Nakano, Y., Ochi, H., ... & Matsuura, M. (2013, August). An autonomous underwater vehicle with a canard rudder for underwater minerals exploration. In 2013 IEEE International Conference on Mechatronics and Automation, 1571-1576, IEEE.

Zang, S., Ding, M., Smith, D., Tyler, P., Rakotoarivelo, T., & Kaafar, M. A. (2019). The impact of adverse weather conditions on autonomous vehicles: How rain, snow, fog, and hail affect the performance of a self-driving car, IEEE Vehicular Technology Magazine, 14(2), 103-111.

Zeeb, K., Buchner, A., & Schrauf, M. (2015). What determines the takeover time? An integrated model approach of driver takeover after automated driving, Accident Analysis & Prevention.

Zeeb, K., Buchner, A., & Schrauf, M. (2016). Is takeover time all that matters? The impact of visual-cognitive load on driver takeover quality after conditionally automated driving, Accident Analysis & Prevention, 92, 230-239.

Zeeb, K., Härtel, M., Buchner, A., & Schrauf, M. (2017). Why is steering not the same as braking? The impact of non-driving related tasks on lateral and longitudinal driver interventions during conditionally automated driving, Transportation Research Part F: Traffic Psychology and Behavior, 50, 65-79.

Zhou, F., Yang, X. J., & Zhang, X. (2020). Takeover transition in autonomous vehicles: A YouTube study, International Journal of Human–Computer Interaction, 36(3), 295-306.

Zihsler, J., Hock, P., Walch, M., Dzuba, K., Schwager, D., Szauer, P., & Rukzio, E. (2016, October). Carvatar: increasing trust in highly automated driving through social cues, In adjunct proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 9-14.

APPENDIX

CCAT Project: Development of Situational Awareness Enhancing Systems for AV-to-Manual Handover and Other Tasks

Published Related Work

Paper 1: Li, Y., Chen, T., Chen, S., Labi, S. (2022). Tradeoffs between safe/comfortable headways versus mobility-enhancing headways in an automated driving environment: preliminary insights using a driving simulator experiment.
Frontiers in Engineering and Built Environment, Volume 1 Issue 2, 173-187.
https://www.emerald.com/insight/content/doi/10.1108/FEBE-05-2021-0025/full/html

Abstract
The anticipated benefits of connected and autonomous vehicles (CAVs) include safety and mobility enhancement. Small headways between successive vehicles, on one hand, can cause increased capacity and throughput and thereby improve overall mobility. On the other hand, small headways can cause vehicle occupant discomfort and unsafety. Therefore, in a CAV environment, it is important to determine appropriate headways that offer a good balance between mobility and user safety/comfort. In addressing this research question, this study carried out a pilot experiment using a driving simulator equipped with a Level-3 automated driving system, to measure the threshold headways. The Method of Constant Stimuli (MCS) procedure was modified to enable the estimation of two comfort thresholds. The participants (drivers) were placed in three categories (Cautious, Neutral and Confident) and 250 driving tests were carried out for each category. Probit analysis was then used to estimate the threshold headways that differentiate drivers' discomfort and their intention to re-engage the driving tasks. The results indicate that Cautious drivers tend to be more sensitive to the decrease in headways, and therefore exhibit greater propensity to deactivate the automated driving mode under a longer headway relative to other driver groups. Also, there seems to exist no driver discomfort when the CAV maintains headway up to 5%–9% shorter than the headways they typically adopt. Further reduction in headways tends to cause discomfort to drivers and trigger takeover control maneuver. In future studies, the number of observations could be increased further. The study findings can help guide specification of user-friendly headways specified in the algorithms used for CAV control, by vehicle manufacturers and technology companies. By measuring and learning from a human driver's perception, AV manufacturers can produce personalized AVs to suit the user's preferences regarding headway. Also, practitioners and researchers could apply the identified headway thresholds to update highway lane capacities and passenger-car-equivalents in the autonomous mobility era. The study represents a pioneering effort and preliminary pilot driving simulator experiment to assess the tradeoffs between comfortable headways versus mobility-enhancing headways in an automated driving environment.