DRIVERS’ HAZARD AVOIDANCE DURING VEHICLE AUTOMATION:
IMPACT OF MENTAL MODELS AND IMPLICATIONS FOR TRAINING

A Dissertation Presented

by

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ABSTRACT

DRIVERS’ HAZARD AVOIDANCE DURING VEHICLE AUTOMATION: IMPACT OF MENTAL MODELS AND IMPLICATIONS FOR TRAINING

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Advanced Driver Assistance Systems (ADAS) are vehicle automation systems that have become more accessible and prevalent in vehicles in recent years. But the introduction of such technologies introduces new human factors challenges. Past literature suggests that users of vehicle automation lack the necessary and appropriate knowledge about their automation system. This may play a negative role in their hazard avoidance abilities when driving with automation features. Improving mental models and knowledge could generally lead to safer interactions with vehicle automation systems, but any effort to develop hazard avoidance skills when driving with vehicle automation is impeded by the lack of literature regarding the subject. Moreover, it is possible hazard avoidance for vehicle automation may actually differ from that for traditional driving. For vehicle automation, system-related changes occurring internally inside one’s vehicle also impact how the system responds and controls the vehicle. Failure to recognize certain critical
system changes may have disastrous consequences. Hence, it is imperative that a new framework for hazard avoidance in the new context of vehicle automation, especially for ADAS features, is conceptualized. Initially, the research focused on realizing exactly this by proposing a conceptual framework for hazard avoidance in the context of vehicle automation by making use of past literary sources on hazard avoidance for traditional driving. Next, the relationship between mental models, training, and hazard avoidance was mapped and each new behavioral construct of hazard avoidance focusing on awareness, detection, and responses based on internal events was assigned potential outcome measure. Next, an observational study was conducted with ten experienced users of Adaptive Cruise Control (ACC). Among them, five were assigned to an eye movements group and five others to a verbal responses group. The eye movement observations gave us insights into how experienced users detect and respond to hazards and how these affect their interactions and responses using their ACC systems. The verbal group also provided insights about the participants’ awareness during the drive which featured several edge-case and normal events. These observations imply that hazard avoidance behaviors actually differ in the context of ADAS compared to traditional driving. The findings from the observational study were leveraged when designing and developing a new training program where drivers would receive an immersive and realistic training experience through a Virtual Reality (VR) headset. The main objective of the training program was to improve the user’s mental models about ACC and also equip them with the necessary skills to avoid hazard during edge case events of ACC. Finally, an evaluation study was conducted with 36 novice ACC users on a driving simulator capable of simulating ACC operations. The participants were equally
and randomly assigned to one of three group – the VR group that received the newly designed VR training program; the SD group that received training material with state diagram visualization of ACC and other information derived from owner’s manuals; or the BI group that received basic textual information about ACC. The participants’ mental models before and after training were measured using a mental models survey, and the simulator drive was designed to collect valuable data about the participants interactions with ACC and their hazard avoidance behaviors. Findings revealed that although the VR training program had some impact on the participants' mental models and hazard avoidance behaviors, the impact was not statistically significant. However, the VR training did show significantly positive influences on the participants’ internal glance activities that detect and assess system states, during edge case events. This finding is important since one of the modules of the VR training program was carefully curated to improve driver’s glance behavior when encountering edge case events of ACC. The results also establish the relationships between training and mental models although no significant correlations were found between the participants’ mental models and their hazard avoidance behaviors. However, this does fill a major gap in literature about our understanding about hazard avoidance in the context of vehicle automation and ADAS and could be extended for ADAS features other than ACC or even higher levels of automation. The VR training program can be built upon to include more ADAS features as well leading to better training practices in a rapidly developing world where vehicle automation has become a mainstay.
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CHAPTER 1.
DISSERTATION OVERVIEW

1.1. PROBLEM STATEMENT

Advanced Vehicle Technologies have become more accessible to road users in recent years, with most automobile companies introducing advanced driver assistance systems (ADAS) into their vehicles (SAE, 2018). By assisting drivers in controlling the vehicle longitudinally and laterally, ADAS features such as Adaptive Cruise Control, Lane Keeping Assistant, etc. aim to improve safety on the roadway (Lindgren & Chen, 2007; Bengler et al., 2014). But the introduction of ADAS and vehicle automation features in general also introduces new human factors challenges, which may be caused due to reduced driver involvement and the need for the driver to get back into the control loop after prolonged inactivity (Seppelt & Victor, 2016). These factors may contribute towards negative behavioral adaptation (Rudin-Brown & Parker, 2004), mode confusion (Wilson et al., 2020), and the driver feeling ‘out-of-the-loop’ (Kaber & Endsley, 1997; Merat et al., 2019).

While previous studies have investigated some of these human factors concerns regarding ADAS features, the effect on drivers’ hazard avoidance has not yet been investigated. Even though some ADAS and vehicle automation features may be able to detect or react to certain on-road events, they may be unable to do so for a wide range of events outside its operational design domain (ODD) (Cho & Hansman, 2020), creating complications in terms of risk assessment and hazard avoidance. But the catch may be that hazard avoidance is not yet understood properly in the context of vehicle automation
and ADAS. This raises the question – “Should hazard avoidance abilities be extended to avoid hazards posed by system failure and the drivers’ failure to recognize certain on-road events that are outside the system’s ODD?” If yes, it would be imperative for the driver to have sufficient knowledge about the system’s functionalities, ODD limitations, and extrapolate this knowledge to avoid hazards when using vehicle automation or ADAS. However, literature suggests that drivers are generally unaware or lack knowledge about their system’s functionalities and limitations (Jenness et al., 2008; McDonald et al., 2018). This may in turn impair their ability to successfully avoid hazards while using ADAS. Past studies have suggested training as one of the solutions towards improving mental models about the system’s operations, functions, and limitations (Beggiato & Krems, 2013; Forster et al., 2019). This may in turn equip them with the necessary system-related knowledge to predict, detect, and mitigate hazards that may occur internally in addition to those that occur externally. However, to design such a training paradigm to improve a drivers’ hazard avoidance, it is prudent to first understand how hazard avoidance for vehicle automation and ADAS differs from hazard avoidance for traditional driving.

1.2. OBJECTIVES OF THE DISSERTATION

The objective of the research is to understand hazard avoidance for vehicle automation, how it will vary when compared to the traditional definition of hazard avoidance, and devise methods to develop and improve these skills in future ADAS users. This dissertation research aimed to answer the following research questions,

1. How does hazard avoidance differ when driving with ADAS?
2. How can training be designed to improve mental models, in terms of content & delivery method (platform)?

3. Does improved quality of mental models through training lead to improvements in the drivers’ hazard avoidance behaviors?

1.3. DISSERTATION RESEARCH PHASES

The dissertation research was undertaken in four research phases. Each phase will contribute to the next phase of research and will have an overarching goal of understanding Hazard Avoidance for vehicle automation and devising training methods to improve those skills in novice users of automation. Each of the phases have been briefly described below along with the relevant tasks and goals.

1.3.1. Framework for Hazard Avoidance in Vehicle Automation

The purpose of the first phase of this dissertation research addressed the question, “How does hazard avoidance differ when driving with ADAS?” and involves conceptualizing a framework for hazard avoidance when driving with vehicle automation. This phase also investigated past literature to understand how hazard avoidance for this new context can be measured using outcome measures as well as realize possible new categories of hazards.

1.3.2. Observing Drivers’ Hazard Avoidance Behaviors

This second phase of research also addressed the research question – “How does hazard avoidance differ when driving with ADAS?” An observational study was conducted on a driving simulator and the goal was to evaluate the conceptual framework from the previous phase by observing drivers’ responses and behaviors when encountering the
hazardous scenarios when driving with Adaptive Cruise Control. The results from this study verified the conceptual framework and provided key insights into the development and design of the training program in the next phase.

1.3.3. Training Methodology - Concept and Design

This third phase of research addressed the question, “How can training be designed to improve mental models, in terms of content & delivery method (platform)?”. A training approach was conceptualized and designed by incorporating behaviors observed from the previous phases. The goal of training was to calibrate drivers’ mental models regarding the functions and limitations of ADAS and educate them about safety critical situations where ADAS will be unable to function properly or fail. This phase also selected the mode of delivery of the training by reviewing literature on different platforms of training and their effectiveness in improving user behavior and knowledge.

1.3.4. Evaluation of Training Method

In the final phase of this research, an experimental driving simulator study was conducted to test the efficacy of the newly designed training program to improve drivers’ mental models and hazard avoidance. By comparing different training platforms, this phase addressed the research question – “Does improved quality of mental models through training lead to improvements in the drivers’ hazard avoidance behaviors?”. 
CHAPTER 2.  
INTRODUCTION

This chapter provides background on advanced vehicle technologies (AVT) and advanced driver assistance systems (ADAS), the recognized human factors challenges in the context of AVT and ADAS. The last section of the chapter will discuss literature on Hazard Avoidance over the last few decades.

2.1. ADVANCED VEHICLE TECHNOLOGIES

Our civilization in many ways is defined by our mode of transportation. One of mankind’s defining invention was that of the wheel, but the invention only found meaning when it was used for transportation purposes in ancient Mesopotamia where stone-paved roadways were constructed for transportation of goods and for travel (Gregersen, 2011; Potts, 2012). Any projection of future human development always goes hand in hand with development in our mode of transportation. In his book ‘Magic Motorways’, Bel Geddes predicted the future of transportation and highway design, and the possibility of self-driving cars where humans would be mere passengers (Geddes, 1940). Another popular science fiction writer, Isaac Asimov, also predicted ‘autonomous vehicles’ in their short story “Sally”, where vehicles had intelligent positronic brains (Asimov, 1969).

Although we have not achieved fully automated, self-driving vehicles yet, there has been rapid development in advanced vehicle technologies over the recent years (NHTSA, 2017), thus changing the way that drivers interact with their vehicles and also how surface transportation policies are shaped (Milakis et al., 2017). These technologies aim to improve roadway safety (Jiménez et al., 2016; Lu et al., 2004) by assisting the
human driver to undertake lateral and longitudinal maneuvers when driving (Bengler et al., 2014; Lindgren & Chen, 2006), thus reducing the driver’s stress and taking more active control responsibilities (Funke et al., 2007). Some advanced vehicle technologies also have capabilities to follow road signage and rules such as speed limits, and also have faster reaction times than human drivers (Fagnant & Kockelman, 2014). Moreover, these technologies also promote a safer, healthier environment by improving fuel efficiency and reducing emissions (Pribyl et al., 2020; Qin et al., 2018).

2.1.1. SAE Levels of Automation

SAE International introduced their “SAE J3016: levels of driving automation” which provides a taxonomy for six levels of driving automation and describes their role in the dynamic driving task (SAE, 2018). The United States Department of Transportation and the National Highway Traffic Safety Administration also adopted these proposed levels in shaping their various policies and guidelines for the future of transportation with automated vehicles (NHTSA, 2017; USDOT, 2018). The SAE J3016 is illustrated in Figure 1. below (SAE, 2018).

J3016 describes Level 0 to Level 2 as driver support features where the driver is still considered to be driving, even if their feet are off the pedals and their hands are not actively steering. Drivers are advised to supervise the functions of the features and intervene when required. Level 0 is manual driving, but with auxiliary warning features such as blind spot monitoring, lane departure warning, etc. (SAE, 2018). These features do not carry out any of the driving tasks and only provide warnings and momentary assistance. Level 1 is when advanced driver assistance systems (ADAS) come into the fold, by helping drivers undertake either a longitudinal control task or a lateral control
task (SAE, 2018). For example, a vehicle equipped with adaptive cruise control is classified as Level 1 or function specific automation (Trimble et al., 2014). If the vehicle is equipped with two or more ADAS features, then it is classified as Level 2 or partial automation or combined function automation (SAE, 2018; Trimble et al., 2014).

![SAE J3016 Levels of Driving Automation](image)

**Figure 1.** The SAE J3016 Levels of Driving Automation

Level 3 to Level 5 have been described as automated driving systems (ADS) features where a driver is not considered to be driving. However, Level 3 may require the driver to manually take back control when requested, especially in event of failure or when the system reaches its operational design domain (ODD), while Level 4 and Level 5 will not require involvement from the driver (SAE, 2018). The difference between Level 2 and Level 3 is Object and Event Detection and Response (OEDR) i.e., the driver is no longer
expected to monitor the roadway while driving (SAE, 2018). Since the system can essentially ‘self-drive’ at Level 3, but also require intervention during traffic and environmental conditions outside its ODD, Level 3 is described as a conditional automation (SAE, 2018). The distinction between Level 4 and Level 5 is that Level 4 may still have situations where the system fails but is able to maneuver itself to safety even without driver intervention, whereas Level 5 is a completely, self-driving automated vehicle system where no intervention is required, and the system will be able to function on all surfaces, locations, and weather conditions. Although these ADS features are of interest, this dissertation research will not focus on it. However, the impact of the research could be translated and built upon for ADS features by future research work.

2.2. HUMAN FACTORS CONCERNS REGARDING ADAS

Advanced Vehicle Technologies are already making strides in the automobile industry but are limited to lower levels of automated driving i.e., ADAS features and Level 2 systems (two or more ADAS features). When using these systems, drivers would need to passively supervise the operation of ADAS, be always attentive and in the control loop. These requirements could raise some human factors challenges with regards to driver performance and driver behavior. Two of the human factors concerns relevant to this research work have been described below.

2.2.1. Gaps in Mental Models

Literature defines mental models as “the rich and elaborate structure which reflects the user’s understanding about the system’s contents, its functionality, and the concept and logic behind the functionality” (Carroll & Olson, 1987). Mental Models also evolve when
the user experiences a situation. Durso & Gronlund (1999) describe mental models as “a representation of the typical causal interconnections involving actions and environmental factors that influence a system’s functioning” (Durso & Gronlund, 1999). Mental models continuously update knowledge stored in long term memory and use this knowledge when encountering previously experienced scenarios or similar scenarios. Since the introduction of ADAS features have been fairly recent, drivers with no experience of using ADAS, and no prior knowledge or awareness of ADAS functions could most probably lack a suitable mental model about ADAS (Beggiato & Krems, 2013; Victor et al., 2018).

Literature suggests that most ADAS users are not accurately aware of their systems’ functions and limitations. Jenness et al (2008) found that out of 370 users of ACC, only about 28% were aware of their system’s functionalities and limitations (Jenness et al., 2008). Another recent study also reported a similar degree of unawareness among users of other ADAS features such as forward collision warning, lane keeping assistant (LKA), etc. (McDonald et al., 2018). The study also reported that only about one in 10 drivers sought more information about their vehicle’s equipped ADAS features, which is in line with another study’s finding that 40% of the drivers did not read the owner’s manual at all, and the other 60% reported to have only read the manual partially (Mehlenbacher et al., 2002). Without prior knowledge and experience of driving with ADAS features, one could assume that drivers lack an appropriate initial mental model (Beggiato & Krems, 2013). Gaps and mismatches in one’s mental models can manifest as driver errors which lead to dangerous consequences when operating ADAS equipped vehicles (Stanton & Salmon, 2009; Victor et al., 2018). This may also lead to mode
confusion, where drivers are unsure or unaware about the mode the system is functioning in, whether it has been engaged, or whether intervention is required (Endsley, 2017; Wilson et al., 2020).

Mental Models are not easy to develop or maintain and may directly affect the user’s trust and acceptance of a particular system (Beggiato et al., 2015; Victor et al., 2018). First, the development of an initial mental model using an owner’s manual may not be ideal since owner’s manuals usually contain too much information that may not be directly relevant to the information the user is seeking (McDonald et al., 2018). Moreover, the framing and content of the owner’s manual may have an impact on the user’s mental model formation as well (Singer & Jenness, 2020). Owner’s manual that do not adequately inform the users about the vehicle limitations may also lead to the user overestimating a system’s capabilities (Singer & Jenness, 2020). While a user could ultimately calibrate their mental models over time and experience, it is highly recommended that they possess an initial mental model either through training or other instructional material which informs the user about the functions and ODD limitations of their system (Beggiato & Krems, 2013; Gaspar et al., 2020).

2.2.2. Deficiencies in Situation Awareness

Situation Awareness (SA) is an important human factors concern not just in the context of ADAS but driving in general. Situation awareness has been defined as “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 future” (Endsley, 1995). While having good situation awareness may not alone be sufficient for appropriate response to
hazards, being situationally aware may allow the driver in their decision-making processing to respond to an oncoming hazard.

Drivers may be disengaged when driving with any form of automated assistance, and their new passive monitoring role may bring them out of the control loop and increase their involvement in secondary tasks or increase driver distraction. This translates into drivers having low SA which could be crucial for partial driving automation that require the driver to intervene when system reaches its ODD limits (Mueller et al., 2021), and having low SA may impede their abilities to monitor the system’s functions and recognize failure events accordingly (Merat et al., 2012; Merat & Jamson, 2009). Merat & Jamson (2009) found that when driving with some form of vehicle automation, drivers responded much later, and their SA was much lower than during manual driving (Merat & Jamson, 2009). Prolonged driving with vehicle automation can also be detrimental to SA due to higher possibility of driver inattention, vigilance decrement, and disengagement (Cunningham & Regan, 2017; Greenlee et al., 2018; Merat et al., 2019). This could make it harder for a driver to detect and perceive hazards especially since for partial or lower levels of vehicle automation, the system may not have abilities to monitor their surroundings, and hence may not be able to provide feedback or warning to the drivers.

Literature suggests SA is strongly linked to hazard perception or anticipation. Horswill & McKenna (2004) stated that “hazard perception could be viewed as drivers’ situation awareness for potentially dangerous incidents in the traffic environment”. One could say that good hazard perception skills arise from being situationally aware as well as having a good mental model of the driving environment, which would actively assist
in the prediction of dangerous situations (Horswill & McKenna, 2004). Gugerty (2011) stated that attention allocation, especially allocation of focal attention was a critical sub-skill in maintaining SA. Without proper allocation of attention and mental resources, a driver may have deficiencies in their monitoring skills, navigation, and hazard anticipation (Gugerty, 2011). This could suggest that having good hazard anticipation skills arise from being able to make accurate decisions towards oncoming situations and having a good mental model about the traffic situations and events, and effectively avoiding hazards when encountered.

2.3. HAZARD AVOIDANCE

2.3.1. Definition of Hazard Avoidance

Hazard Avoidance has been defined as a blanket term for a collective, continuous set of behaviors that drivers need to exhibit in order to safely drive on the roadway (Pradhan & Crundall, 2017). These behaviors include Hazard Perception, Hazard Anticipation as well as Hazard Mitigation. Horswill & McKenna (2004) defined Hazard Perception as the ability to read and anticipate forthcoming hazardous events on the roadway (Horswill & McKenna, 2004) and it could be stated that Hazard Perception could be the combination of two skills: abilities to anticipate roadway events; and abilities to confirm and evaluate possible risks that may arise from these events. Vlakveld (2011) argued that the term ‘Hazard Perception’ may be flawed as mere perception of hazards is not enough, and drivers would need to consider their subsequent actions if they did perceive a hazardous scenario (Vlakveld, 2011). For example, when a driver approaches a hidden driveway, perceiving the hidden driveway’s existence is not so much important as anticipating what hazards may materialize from it (such as a vehicle pulling out or child running on to the
road), and also being prepared to act if something does indeed materialize. Hence, Vlakveld (2011) suggested that ‘Hazard Anticipation’ is a much better term and had the following three levels: first, would be perceiving the possible hazards by scanning for events on the roadway that may compromise safety; second would be recognizing and confirming a potential hazard event, which could be derived from past experiences or through other factors such as knowledge of traffic rules or reactions of other drivers towards the event; third would be predicting the development of the event and its potential consequence as well as executing appropriate mitigatory actions (Vlakveld, 2011). The latter skill could be defined as ‘Hazard Mitigation’, which seeks to reduce the risks posed by the recognized hazard. Thus, a driver with optimal hazard perception, hazard anticipation, and hazard mitigations skills will be able to recognize potential threats by searching and heeding cues, and scanning for emergent threats, maneuvering their vehicles appropriately to avoid or mitigate materialized hazards. Pradhan & Crundall (2017) suggested that these behaviors exhibited by the driver can be largely bracketed into a blanket term known as ‘Hazard Avoidance’ (Pradhan & Crundall, 2017).

2.3.2. Associated Driver Behavioral Constructs

Hazard avoidance could constitute of several intertwined driver behavioral constructs that involve detecting a hazard, processing and appraising its consequences and effects, and making an appropriate response to avoid collisions or other negative effects the hazard may pose. Pradhan & Crundall (2017) argued that in order to properly define the term ‘hazard avoidance’, it may also be vital to consider the importance of vigilance towards possible hazards along with the aforementioned behavioral constructs, since lack of vigilance may impede the drivers’ ability to respond to any oncoming hazards. Next,
visual search may be another behavioral aspect that is vital to avoiding hazards. This component could be determined by the salience of the hazards on the roadway (color, movement, contrast, visibility, etc.) and the drivers’ search pattern during driving (wider or narrower scanning, dispersion of glances, etc.). Past studies have illustrated the importance of salience of roadway objects and their ability to attract attention of the driver (McCarley et al., 2014). It is important to note that, although salience of hazards could grab the attention of the driver, this is by no means effective if hazards lie outside the drivers’ visual search area. It is well documented by past studies that young, inexperienced drivers have narrower search patterns than their experienced counterparts and lack the ability to anticipate oncoming hazards (Pradhan et al., 2005; Underwood et al., 2002). This is in part due to the lack of knowledge of on-road situations or events that are usually built up and updated in one’s mental model through experience (Horswill & McKenna, 2004). Younger drivers also fixated slower on environmental cues and were also less likely to look at them (Pradhan et al., 2005). Failure to heed cues could result in missing out on subsequent hazards as well.

Hazard Cues serve as precursors towards upcoming hazards, that may invoke a response from drivers and prepare them to avoid hazards. Environmental elements often serve as hazard cues in terms of locations that may be obscuring the drivers’ visual scene, a curved roadway, vegetation covering traffic control devices, etc. (Crundall, 2016). In many cases, traffic control devices also serve as hazard cues that invokes a scanning response from drivers. This can be seen in ‘Hidden Driveway Ahead’ or ‘Stop Sign Ahead’ or ‘Curved Road ahead’ signs, that are placed well in advance of problematic roadway sections that will require the driver to be aware of hazards that may materialize.
at these sections. Hence, the importance of recognizing and heeding hazard cues is indeed important towards predicting and detecting oncoming hazards. A driver who recognizes the appropriate hazard cues, uses the information gained from them as potential hazard evidence for existence of hazards, and plans to prepare themselves to avoid the subsequent hazards.

This brings us to the materialization of the hazards themselves. A latent hazard is a potential hazard that will not necessarily develop into an imminent threat (Vlakveld, 2011). Abrupt hazards are more unpredictable and will present themselves abruptly with no warning or cues. These types of hazards will depend mainly on the drivers’ reaction time to such sudden events. Hazards that are not abrupt or latent materialize after the hazard cues, and the drivers will process the information they have retrieved from their scanning of the visual scene (Pradhan & Crundall, 2017). Drivers will usually use the information received from a detected hazard event in order to understand its consequences and thereby plan on how to mitigate them if necessary. Proper hazard response evaluation skills will be useful for the driver to evaluate the degree of complexity required for hazard mitigation. An experienced driver will be able to process and evaluate hazards events faster and more efficiently than novice drivers and hence successfully mitigate them as well. Studies have shown even when novice drivers do identify hazard cues and successfully detect hazards, they are unable to properly evaluate the complex skill-dependent nature of the response required to mitigate the threats (Horrey et al., 2015). This is also concerning partly due to the possibility that younger; novice drivers may lack the appropriate mental models about traffic situations which is usually developed and updated through experience.
The relation between mental models and hazard avoidance could suggest that to improve one’s hazard avoidance skills, one would need considerable driving experience to experience enough roadway situations and feed it into their mental models. Many studies have indicated training can also improve a driver’s hazard perception or anticipation abilities (Horswill, 2016a; Madigan & Romano, 2020; Pradhan et al., 2005b; Vlakveld, 2011). It has been argued that for most of these training interventions, the theoretical premise has been to utilize training to improve the drivers’ mental models of the traffic environment (Horswill, 2016b).

Literature strongly suggests a link between Hazard Avoidance and Mental Models. However, in the context of vehicle automation, this may differ in many ways. With the system handling most driving tasks, the drivers’ mental workload is reduced (De Winter et al., 2014), with more mental resources available for other tasks, usually non-driving related tasks (Naujoks et al., 2016). This reduced allocation of attention to the active driving task could result in the drivers being ‘out of the loop’ (Merat et al., 2019) and unable to attend to hazardous situations (Louw & Merat, 2017). It was shown that regaining situation awareness was especially harder in time-critical situations in terms of avoiding crashes (Van Den Beukel & Van Der Voort, 2013). This relation between situation awareness and timely takeover from the system could be worsened if drivers’ over-relied on their systems and fail to recognize takeover situations, due to them lacking appropriate knowledge about the system’s ODD limits (Van Den Beukel & Van Der Voort, 2013), or in other words, having gaps and mismatches in their mental models about the system’s capabilities and limitations. Hence, the change in the role of mental models when driving with vehicle automation features will no doubt affect the nature of
Hazard Avoidance when driving with these systems. The next chapter will detail how drivers’ Hazard Avoidance may differ in the context of vehicle automation and how a framework for hazard avoidance can be conceptualized.
CHAPTER 3.

FRAMEWORK FOR HAZARD AVOIDANCE IN VEHICLE AUTOMATION

This chapter will detail the research that was undertaken in order to understand how hazard avoidance differs in the vehicle automation domain when compared to traditional hazard avoidance for manually driven vehicles. A conceptual framework was proposed outlining the relationship between mental models and behavioral components of hazard avoidance in this new context. Lastly, the chapter also focuses on categorizing hazards in this new context and how different behavioral constructs of hazard avoidance can be measured.

3.1. CONCEPTUAL FRAMEWORK FOR HAZARD AVOIDANCE

The onset of vehicle automation may complicate Hazard Avoidance and associated skills. Since the driver is not actively in the control loop, they may experience a significant underload when driving with vehicle automation such as ADAS features (Rudin-Brown & Parker, 2004), as opposed to conventional driving when the driver is always in the loop and is continuously monitoring the roadway under complete synchrony with their driving task. Upon successful detection of a threat, they can immediately respond and mitigate the threat if their hazard avoidance skills are well developed and calibrated (Pradhan & Crundall, 2017). However, when driving with vehicle automation, majority of the tasks are performed by the system and driver is supposed to be monitoring the vehicle, and even if they are appropriately aware of their surroundings, there is a chance that are not appropriately aware of their system’s status and may fail to intervene. Hence, in the context of driving with vehicle automation, it may not be sufficient to only consider the on-road events, since the in-vehicle system-related changes are now equally critical.
ADAS features usually consist of multiple states (Pradhan et al., 2020), and it is important for the driver to be always aware of the current state of their systems. In this regard, it is very important for the driver to have sufficient knowledge of the system’s functions and limitations. Mental models about on-road situations and hazards are known to be vital in successful hazard avoidance (Horswill & McKenna, 2004). In the context of vehicle automation, this would extend to having well-calibrated mental models about system’s functions and limitations.

The conventional model of hazard avoidance has been based on Endsley’s situation awareness model which comprises of three levels: perception, comprehension, and prediction (Endsley, 1995). Michon (1985) introduced a framework that divided driver behavior into strategic, tactical, and operational levels (Michon, 1985). Pradhan & Crundall (2016) argued that by combining both Michon’s and Endsley’s models a suitable framework for hazard avoidance could be conceptualized while accounting for constructs of cognition, perception, processing, and action (Pradhan & Crundall, 2017). This framework could serve as a foundation for updating hazard avoidance in the new context of vehicle automation.

Traditionally, i.e., with manual driving, hazard avoidance has been related to concepts of environmental awareness and traffic knowledge, elements that have been previously well studied (Horswill & McKenna, 2004; Pradhan & Crundall, 2017). However, the presence of vehicle automation (such as ADAS or ADS) changes the driving task and the driver’s responsibilities, and as an extension, their hazard avoidance skill requirements. For example, with vehicle automation systems handling many driving tasks, the drivers’ mental workload is reduced (De Winter et al., 2014), making more
mental resources available for other non-driving related tasks (Naujoks et al., 2016). This results in the drivers being ‘out of the loop’ (Merat et al., 2019) and unable to attend to hazardous situations (Louw & Merat, 2017). Another example is regarding system knowledge. Vehicle automation systems are inherently complex, and drivers may lack appropriate knowledge about these systems (Jenness et al., 2008; Singer & Jenness, 2020), i.e., low quality mental models. This will have a negative impact on drivers’ interactions with the systems. This underscores the importance of understanding the relationships between Mental Models and Hazard Avoidance in the context of ADAS. While it may be of interest to do the same for ADS, it is more urgent to do so in the context of ADAS, since they are quickly becoming standard features in everyday vehicles. The conceptual framework presented in Figure 2, attempts to relate elements of the concepts of Mental Models and Hazard Avoidance in the context of ADAS.

Figure 2. Conceptual Framework of Hazard Avoidance in the context of ADAS
Hazard Avoidance for ADAS can be conceptualized as differing from ‘traditional’ Hazard Avoidance (for manual driving). In terms of awareness, traditional Hazard Avoidance is related to Environmental Awareness, i.e., the driver’s awareness of the traffic environment such as external vehicles, road geometry, signs, road users, etc. However, for automation, internal events such as system status and state changes indicated by display icons, audible alerts, notifications, etc. will play a role in how the automation system controls and maneuvers the vehicle. Therefore, System Awareness, which is the driver’s awareness of the status of the system, will also be important and adds a new layer to the drivers’ awareness requirements. This may be influenced by their knowledge about system states and what can cause the system status to change. Perception in the context of driving has been described as collecting and interpreting visual information gained from the immediate environment (Kemeny & Panerai, 2003). Perception includes – lookout behaviors - the driver’s visual scanning for information, detecting changes and events of interest, and predicting future events by processing the information collected. In the context of ADAS, a driver will also need to collect and interpret information about their system, from in-vehicle cues and displays, in addition to information from their immediate driving environment. A successful response is usually the outcome of successful hazard avoidance (Pradhan & Crundall, 2017). When driving with vehicle automation, responses could involve vehicle control (steering, slowing down, etc.) or system control (change ADAS/automated system parameters, engage/disengage, turn on/off, etc.) or a combination of both.

Further, the conceptual framework seen in Figure 2 suggests there exists a relationship between mental models about ADAS and elements of Hazard Avoidance. A
driver’s completeness and accuracy of their mental models about ADAS could be vital for system awareness, given that their mental models will frame their knowledge and expectations of system behaviors. For the same reason, the quality of mental models may similarly influence the driver’s lookout behaviors. Mental models also influence the driver’s knowledge about how to operate the system at different states and about the correct actions/responses to change the state of the system. Hence, the quality of mental models may also impact driver responses in terms of system control. Mental models can be influenced by preconceptions, knowledge, experience, system design, and training. Research shows that training improves mental models about ADAS or vehicle automation (Beggiato & Krems, 2013; Forster et al. 2019a; Forster et al., 2019b; Noble et al., 2019).

However, there is very sparse, if any, evidence of the impact of improved mental models about vehicle automation through training, and associated improvement in hazard avoidance behaviors in drivers. This could be due to the lack of literature regarding hazard avoidance in the context of vehicle automation. Moreover, understanding hazard avoidance in this new context will also require developing methods to improve driver’s hazard avoidance. The conceptual framework suggests that training affects mental models and that there is a direct relationship between mental models about vehicle automation systems and elements of hazard avoidance. Hence, it is of particular interest to establish these relationships between training, mental models, and hazard avoidance in the context of ADAS through empirical research.

3.2. UPDATING THE FRAMEWORK WITH OUTCOME MEASURES
Several new behavioral constructs related to hazard avoidance were conceptualized in the framework presented in Figure 2. The obvious next step required to further update the
framework would be to understand them from a measurement perspective, i.e., how could the newly proposed constructs be measured during, let’s say, an empirical study. In the framework, one could speculate that System Awareness is influenced by the driver’s knowledge about system states and operations. System awareness described in the framework should not be confused with the concept of ‘Situation Awareness’ which constitutes a much broader set of behaviors such as awareness about weather, route, etc. and allocating and maintaining attentional resources towards roadway and surroundings (Gugerty, 2011). However, from a measurement perspective, it is possible to leverage measurement processes from the situation awareness literature to measure system awareness. This is especially critical since literature has a major gap about measures for system awareness.

Awareness has generally been measured through user narratives, probes, or using self-reported ratings. Therefore, one potential technique to understand driver’s awareness about their system states is to have them provide a user narrative in form of running commentary of the system’s status as well as instances of system state change (Walker et al., 2008). It is also possible to gauge the driver’s system awareness by utilizing a rating technique similar to the Situation Awareness Rating Technique (SART) which has been used in the past to gauge the users’ awareness to particular situations or scenarios (Endsley et al., 1998; Walker et al., 2008). However, SART is a self-reported rating technique, and as with all self-reported responses, it may have reliability issues and suffer from user bias (Schacter, 1999). Parasuraman et al (2009) showed that it is possible to use task-based probes to measure the users’ awareness for task specific actions that could result in change of system states (Parasuraman et al., 2009). Other probing techniques
involve freeze probes where a particular frame of the simulation or video is frozen and
the users are probed about specific situation-related queries (Lindemann et al., 2018;
Walker et al., 2008). Many freeze probes are based on or adapted from the Situation
Awareness Global Assessment Technique (SAGAT) (Endsley, 1988; Endsley et al., 1998).
However, freeze probes carry the disadvantage of breaking the dynamic simulation and
the realism of the simulation. Given the shortcomings of freeze probes and self-reported
rating techniques, user narratives in form of running commentary (Walker et al., 2008) or
task-specific probes (Parasuraman et al., 2009) in real-time while driving with vehicle
automation may prove to reliable and useful measures to characterize drivers’ system
awareness.

For perception, drivers’ lookout behaviors can be characterized by their eye
movements. Drivers’ fixation behaviors such as their mean fixation duration and the
frequency of fixations are some of the widely used metrics to understand drivers’
perception behaviors (Stephenson et al., 2020). However, it could be important to note
that driving with ADAS may involve various areas of interest (AoI), both internally
within the vehicle and in the immediate external environment. Due to this, measures such
as percentage time spent at each AoI and number of visits per AoI (Navarro et al., 2019),
and visit duration within each AoI (Stephenson et al., 2020; Zhou et al., 2018), may prove
to be more relevant where the term ‘visit’ refers to the act of fixating one’s gaze at an AoI
or at different elements within the AoI. The users’ detection and prediction behaviors
could be characterized by their reaction times such as the “time taken to make first
fixation at AoI” (Stephenson et al., 2020). Other eye measures such as gaze dispersion
can also help understand the driver’s lookout behaviors when driving, by taking the
standard deviation of the yaw and pitch of their gaze directions into consideration (Goncalves et al., 2019; Goncalves et al., 2020; Louw et al., 2017; Louw & Merat, 2017). Percentage gaze at road center could also be utilized understand drivers’ lookout behaviors towards the forward roadway (Goncalves et al., 2020; Jamson et al., 2011; Metz et al., 2021). Therefore, in order to measure drivers’ perception behaviors, eye metrics based on or related to gaze fixations locations and durations can be used.

As mentioned earlier, for driving with vehicle automation (or ADAS) responses could involve vehicle control (steering, slowing down, etc.) or system control (change ADAS parameters, engage/disengage, turn on/off, etc.) or a combination of both. In a previous work, the different modes of ADAS were characterized as states where each state represented a unique function of the ADAS feature in use (Pradhan et al., 2020, 2021). The state changes can be monitored using the vehicle data obtained from the driving simulator and could be useful when understanding response times and accuracy of responses. Measuring the participants’ response time, i.e., their reaction times at predefined scenarios or locations may be useful in determining their success at system control (Stanton et al., 2011). Since system control will almost certainly involve actions to be performed by the driver in response to hazards, their actions could be binary coded – “performed required action” or “did not perform required action” (Schleicher & Gelau, 2011) and the accuracy of their actions can also be measured, such as, changing parameters to particular values (Schleicher & Gelau, 2011). Past studies have also looked at error identification as a possible technique to measure drivers’ control abilities by monitoring driver errors (Banks et al., 2018; Barrash et al., 2010; Khattak et al., 2021; Young et al., 2013). Since our previous work has already identified and categorized
operator errors while driving with ADAS (Pradhan et al., 2020, 2021), error identification and measurement of the accuracy of driver actions could serve as ideal outcome measures for system control. With this knowledge, the framework from Figure 2. been updated to include the selected outcome measures for each individual behavioral construct of hazard avoidance for ADAS as discussed in the last section. This updated framework can be seen below in Figure 3.

Figure 3. Conceptual Framework updated with potential outcome measures for each behavioral component of Hazard Avoidance

3.3. HAZARD CATEGORIES

For manual driving, the categories of hazards that a driver could encounter during driving are almost entirely environmental threats that warrant response from the driver in form of vehicle control. In the presence of vehicle automation or ADAS, hazards due to system
failure or inability of the system to function optimally which require responses in the form of system control will also need to be considered. These system-related threats may manifest internally within the vehicle in the form of internal alerts or internal signifiers. This will require the driver to have appropriate system awareness and perception skills to detect such events and predict outcomes, and finally respond in terms of system control by performing the necessary operational tasks such as pressing buttons, engaging or disengaging the system, assuming manual control of the vehicle, etc. Hazards in the context of vehicle automation will therefore not only include those encountered during manual driving but also an additional variety of hazards that are brought forth by the limitations of the ADAS features in use.

Some examples of hazards relevant for driving with ADAS have been described and listed in Table 1. In this table, the terms “signifiers” or “cues” refer to the precursors towards upcoming hazards, that may invoke a response from drivers and prepare them to avoid hazards. For manual driving, environmental elements often serve as precursors in terms of locations that may be obscuring the drivers’ visual scene, a curved roadway, vegetation covering traffic control devices, etc. (Pradhan & Crundall, 2017). For vehicle automation, precursors will also include internal alerts, notifications, icons, etc. These internal signifiers or cues may indicate a system state change – such as system deactivation. When driving with vehicle automation, a driver should also lookout for both internal and external signifiers or cues and use the information gained to detect or predict the existence of potential threats and respond accordingly.
<table>
<thead>
<tr>
<th>No.</th>
<th>Example</th>
<th>Signifiers/Cues</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>The driver has set the speed of the Adaptive Cruise Control at 45 MPH which is the posted speed limit near an intersection. Any potential cross-traffic is a hazard in this scenario.</td>
<td>The driver will have to lookout for external signifiers or cues such as lead vehicles changing lanes swerving or road signage for any emerging cross traffic. They will also need to be aware of any corresponding system related changes.</td>
</tr>
<tr>
<td>2</td>
<td>Lane Keeping Assistant will not be able to detect vulnerable road users (VRU) sharing lanes with the driver and may nudge the vehicle back into the center when attempting to yield to the VRUs.</td>
<td>The driver will have to lookout for external signifiers or cues such as road signage indicating shared lanes and detect any VRUs sharing lanes with them. They will also need to be aware of any corresponding system related changes.</td>
</tr>
<tr>
<td>3</td>
<td>If there is a static object such as debris, a driver travelling with LKA active may have to turn on their blinkers to change lanes.</td>
<td>The driver will have to lookout for external signifiers or cues such as lead vehicles changing lanes to avoid objects or road signage for static roadway objects. They will also need to be aware of any corresponding system related changes.</td>
</tr>
<tr>
<td>4</td>
<td>ACC has difficulties detecting lead vehicles at sharp curves, causing it to revert to previous set speed.</td>
<td>The driver will have to lookout for internal signifiers or cues from the instrument panel to detect the system’s failure to detect the lead vehicle when inside the curved section.</td>
</tr>
<tr>
<td>5</td>
<td>A lead vehicle travelling at slower speeds changes lanes reverting the ACC to previous set speed.</td>
<td>The driver will have to lookout for internal signifiers or cues from the instrument panel to detect the state change.</td>
</tr>
<tr>
<td>6</td>
<td>For LKA, lack of lane markings or faded lane markings can cause the system to deactivate abruptly or temporarily.</td>
<td>The driver will have to lookout for internal signifiers or cues from the instrument panel to detect the state change or deactivation of LKA.</td>
</tr>
</tbody>
</table>
3.4. IMPLICATIONS ON DISSERTATION RESEARCH AND NEXT STEPS

3.4.1. Hypotheses

The framework proposed in this chapter helps to generate the following hypotheses (highlighted by blue lines in the framework) which is examined and tested for the next research phases of this dissertation.

H1. Training impacts the drivers’ mental models about ADAS

H2. The Training platform (mode of delivery) has an impact on the driver’s mental model

H3. Training affects driver’s mental model which in turn affects their System Awareness

H4. Training affects driver’s mental model which in turn affects their Lookout Behaviors

H5. Training affects driver’s mental model which in turn affects their System Control skills

3.4.2. Research Questions

The research conducted in the subsequent chapters aim to ultimately answer the following research questions,

1. How does hazard avoidance differ when driving with ADAS?

2. How can training be designed to improve mental models, in terms of content & delivery method (platform)?

3. Does improved quality of mental models through training lead to improvements in the drivers’ hazard avoidance behaviors?

To answer the above questions, the research was undertaken in a phased manner, as described in the next sections.
3.4.3. Observing Drivers’ Hazard Avoidance Behaviors

An observational study was conducted on a driving simulator with the goal of evaluating the proposed conceptual framework. The methods and findings from this study have been described in Chapter 4.

3.4.4. Training Methodology – Concept and Design

Training content was conceptualized and developed to improve the quality of a drivers’ mental models about ADAS and their hazard avoidance behaviors. The training content was based on existing literature on training and also identified suitable modes of delivery for the training. The methods and practices involved in developing the training program to have been explained in Chapter 5.

3.4.5. Evaluation of Training Method

An experimental driving simulator study was conducted to test the efficacy of the newly designed training method. The methods, experimental design, and results have been included in Chapter 6 and have been discussed in Chapter 7.
CHAPTER 4.

OBSERVING DRIVERS’ HAZARD AVOIDANCE BEHAVIORS

This chapter entails the methodologies and findings from the observational study conducted to observe driver behaviors, actions, and responses when driving through scenarios with hazard events categorized in the previous chapter. The main objective of this observational study was to verify the conceptual framework from the previous chapter and broaden our understanding about how drivers respond to hazards when driving with ADAS. There is a major gap in literature regarding how hazard avoidance differs in the context of ADAS driving. Unlike traditional driving where hazards are almost entirely external, ADAS driving introduces the role of system’s status and changes. This study aimed to understand drivers' hazard avoidance behaviors, when driving with Adaptive Cruise Control (ACC), by observing their eye movements, system interactions, and verbal narratives. The observations suggest that hazard avoidance behaviors actually differ in the context of ADAS compared to traditional driving. These insights could be used to design and develop appropriate training methods to improve drivers’ hazard avoidance skills and mental models when driving with ADAS features.

4.1. RESEARCH MOTIVATION AND OBJECTIVES

4.1.1. Motivation for the Observational Study

In previous chapters, the term ‘Hazard Avoidance’ has been defined as a blanket term for a collective, continuous set of behaviors that involve detecting a hazard, process and appraise its consequences and effects, and make an appropriate response to avoid collisions or other negative effects the hazard may pose. Past studies mention that inexperienced drivers have narrower search patterns than their experienced counterparts.
and lack the ability to predict and anticipate oncoming hazards (Crundall, 2016, Underwood et al, 2002; Pradhan et al, 2005). This was speculated to be due to the lack of on-road situations or events in a novice or younger driver’s mental models, that are usually built up and updated through experience (Horswill & McKenna, 2004; Durso et al, 2017; Gugerty, 2011). This relationship between mental models and hazard avoidance becomes problematic in the context of driving with ADAS, since ADAS features are often complex, and users may lack appropriate mental models, i.e., knowledge and understanding about the systems’ functions and limitations (McDonald et al, 2018).

While this creates an urgent need for devising appropriate methods to improve one’s hazard avoidance when driving with ADAS, there is a major gap in literature about how hazard avoidance differs when driving with ADAS. Unlike manual driving, where precursors for hazards are almost exclusively external (Pradhan & Crundall, 2017), for ADAS driving, these precursors will also need to include internal elements such as instrument panel icons, in-vehicle alerts, etc. as well as general awareness of the system’s status and operations.

4.1.2. Objectives of the Observational Study

The aim of this study was to understand drivers' hazard avoidance behaviors, when operating Adaptive Cruise Control or ACC, by observing drivers' eye movements, system interactions, and verbal narratives. Adaptive Cruise Control is an ADAS feature that assists the driver by maintaining the vehicle’s speed and its distance from the vehicle in front (Xiao & Gao, 2010) and is one of the most widely used ADAS features (Palac et al, 2021). The conceptual framework from Chapter 3 was helpful in selecting the specific observation metrics for this observational study. Eye movements were observed since
hazard perception and/or hazard anticipation has traditionally been determined by examining the driver’s eye movements towards hazardous elements and events on the roadway, and by examining their action-based responses to said hazardous events. Observation of verbal responses have been included to understand the driver’s awareness of the ongoing events as well as their awareness of the system status when driving with ACC.

4.2. METHODS

4.2.1. Participants

4.2.1.1. Recruitment Criterion

Ten participants aged 25 to 55 years old (mean = 28.1; SD = 5.195) with a valid US driver’s license were recruited for this study. Since, the goal of this study was to observe drivers’ hazard avoidance behaviors when driving with ADAS, younger populations (aged 18 to 24 years) were excluded from the recruitment process, since literature suggests that inexperienced drivers do not possess the appropriate hazard anticipation abilities compared to their experienced counterparts (Crundall, 2016, Underwood et al, 2002; Pradhan et al, 2005). In addition to the age restrictions, participants’ familiarity and experience using ACC were established by using a screening survey prior to study participation. Only those participants who self-reported being appropriately familiar and had prior experience using ACC were included in the study. Institutional Review Board approval was also sought and granted for conducting the study.
4.2.1.2. Participant Groups

The recruited participants were randomly and equally assigned to one of the two groups: Verbal Response group or the Eye Movements group. The participants in the Verbal Response group were required to provide a running commentary (Walker et al., 2008) during their simulator drive, while the participants in the Eye Movements group had their eye movements continuously monitored using an eye-tracking device. The Verbal Response group also received an audio-based question about the system status at the end of each event in the simulator drive to monitor their awareness of the ACC system’s status and functions (Parasuraman et al., 2009).

4.2.2. Equipment & Apparatus

4.2.2.1. RTI Fixed-Base Driving Simulator

The study utilized the Realtime Technologies (RTI) full-cab driving simulator (Figure 4) in the UMass Human Performance Lab, which is a high-fidelity fixed-base driving simulator running on RTI’s SimCreator engine. The simulator consists of a 2013 Ford Fusion cab and five screens situated in front of the cab giving the driver a 330-degree field of view. The simulator also projects the rear views of the simulator environment with the help of two dynamic side mirrors and a rear-view mirror. A five-speaker surround system simulates external environmental sounds and two-speakers simulate in-vehicle noise. The SimCreator engine enables the designing and scripting of edge-case events, as well as audio cues which provide navigational directions to the driver within the virtual world. The SimADAS package within the SimCreator engine enables the simulator to include several ADAS features (such as ACC). In this study, the ACC system utilized functionalities and limitations mirroring those of ACC systems found in the real
world and could maintain the vehicle’s speed and distance from the lead vehicle based on the drivers’ defined settings. The SimObserver feature records the driver’s hand and foot movements as well as verbal responses using video cameras.

4.2.2.2. **ASL MobileEye**

The Applied Science Laboratories (ASL) MobileEye is a monocular eye tracker consisting of a pair of goggles with one camera focused on the eye, another focused on the scene ahead, and a small reflective monocle for the eye camera to view the eye without obstructing the participant’s view. Calibration is conducted using a 9-point calibration screen. Eye movements are recorded at a 30 Hz refresh rate and the gaze cursor is overlaid on the recorded video output. The eye tracker has an accuracy of 0.5 degrees of visual angle.

4.2.3. **Scenarios**

Six ‘edge-case’ events and two ‘normal’ events were included in the simulator drive as scenarios. In this study, ‘edge-case’ events are those driving situations where ACC can no longer operate appropriately due to the system having reached its ODD limits. Meanwhile, ‘normal’ events are those driving situations where ACC is expected to operate appropriately as intended. At the beginning of the simulator drive, an ACC activation audio cue – “Remember to activate Adaptive Cruise Control”, was provided to
the participants. Participants also received navigational audio cues during the drive. As mentioned before, the Verbal Response group also received an audio-based question about the system status at the end of each event. Another detail to note is that all the lead vehicles featured in the drive were scripted to pull over at the end of every scenario for route design and planning purposes. The order of appearance and description of events during the simulator drive can be seen in Table 2.

4.2.4. Study Procedure

Upon their arrival in the lab, the participants provided their informed consent for participation in the study. Following this, the participants filled out a demographics questionnaire. They were then provided with a short practice drive on the driving simulator, lasting no more than five minutes. This practice drive allowed the participants to familiarize themselves with the virtual world and the controls of the simulator cab and the simulator’s ACC system. The Verbal Response group were asked to provide a running commentary about their actions and perceptions about the system status, in-vehicle alerts or changes on the instrument panel, environmental events, etc. The Eye Movements group drove without any such requirement and were outfitted with the head-mounted eye-tracker. The participants were then presented with the main simulator drive (described in Table 2). Upon completing the drive, participants were compensated for their visit.
### Table 2. Event Occurrence & Descriptions

<table>
<thead>
<tr>
<th>Order</th>
<th>Event Name</th>
<th>Event Type</th>
<th>Event Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Following Lead Vehicle</td>
<td>Normal</td>
<td>The driver approaches a lead vehicle on a divided freeway (speed limit – 65 mph) and ACC maintains the desired Set Distance from it</td>
</tr>
<tr>
<td>2</td>
<td>Traffic Cones</td>
<td>Edge-Case</td>
<td>The driver approaches a transitional area to an undivided roadway with decreased speed limit (50 mph) and traffic cones on the shoulder</td>
</tr>
<tr>
<td>3</td>
<td>Construction Zone</td>
<td>Edge-Case</td>
<td>The driver approaches a construction zone on the opposite side of the road where an oncoming car also approaches the construction zone</td>
</tr>
<tr>
<td>4</td>
<td>Lead Vehicle &amp; Sharp Curve</td>
<td>Edge-Case</td>
<td>The driver encounters a lead vehicle when travelling inside a sharp curved roadway section</td>
</tr>
<tr>
<td>5</td>
<td>Divided Freeway Transition</td>
<td>Normal</td>
<td>The driver enters a transitional area where the undivided roadway changes to a divided freeway with increased speed limit (65 mph)</td>
</tr>
<tr>
<td>6</td>
<td>Straddling Lead Vehicle</td>
<td>Edge-Case</td>
<td>The driver encounters a lead vehicle that is straddling the lane lines</td>
</tr>
<tr>
<td>7</td>
<td>Oversized Lead Vehicle</td>
<td>Edge-Case</td>
<td>The driver encounters an oversized, slow moving lead vehicle</td>
</tr>
<tr>
<td>8</td>
<td>Parked Truck &amp; Lead Vehicle</td>
<td>Edge-Case</td>
<td>The driver approaches a lead vehicle and ACC initially maintains the desired Set Distance from it. However, the lead vehicle suddenly swerves onto the left lane upon reaching a parked truck on the shoulder.</td>
</tr>
</tbody>
</table>

### 4.2.5. Observation Methods

The observations for the Eye Movements group were derived solely from the eye-tracking video output which showed each participants’ eye movements through an eye-tracking cursor overlaid on the recorded video of the drive seen from the participants’ point-of-view. The videos were analyzed frame-by-frame to observe the changes in the participants’ gaze fixations on different areas of interest and elements within each event in the drive. Videos of the participants’ drive as seen from the eye-tracking video output were also used to derive the context within each scenario. For example, a situation described as “upon encountering the lead vehicle” was derived by observing the lead
vehicle materialize in the scenario as seen in the recorded video. This approach was also used to provide context to participants’ actions such as ‘turning on’, or ‘engaging/disengaging ACC’, by observing said actions in the recorded videos.

As for the Verbal Response group, the participants’ verbal responses and responses to the audio-based questions were recorded through the simulator’s audio recorder and were transcribed into text. The observations for this group were then derived from the resulting text-based transcript. From the transcript, participants’ narratives were categorized for ‘action’, ‘awareness’, ‘prediction’, and ‘expectation’. An example for deriving action, awareness, prediction, and expectation from the participants’ narratives can be understood from the deconstructing following statement into the above categories – “There’s something else in front of me, it’s like a truck. I have the distance set to far away, so it should deactivate soon. I’m gonna put the brakes on if it doesn’t deactivate”. From this statement, the participants’ action (setting the distance), awareness (current Set Distance setting and presence of a lead vehicle), expectation (ACC to deactivate), and prediction (brakes required if ACC does not deactivate) can be derived.

4.3. OBSERVATIONS

The observations for each of the events encountered by the participants in the simulator drive have been described below. Observations also include participants’ initial responses to the ACC activation audio cue which was placed at the beginning of the simulator drive.
4.3.1. Observations For ACC Activation Audio Cue

4.3.1.1. Eye Movements group

There were 16 interactions with ACC observed for all five participants of the Eye Movements group during the initial ACC activation following the audio cue. Out of these, 10 interactions featured participants fixating their gaze solely on the IP. When Switching On ACC, three participants glanced exclusively at the instrument panel (IP) of the simulator cab. Two others alternated their glances between the forward roadway and the IP. While engaging ACC, four participants glanced exclusively at the IP, while one alternated their glances between the forward roadway and the IP. Three participants glanced exclusively at the IP when selecting their Set Speed, while two others alternated their glances between the forward roadway and the IP. Only one participant changed their Set Distance, alternating their glances between the forward roadway and the IP while doing so.

4.3.1.2. Verbal Response group

Two drivers described manually speeding to the required speed for ACC activation. One driver described their expectation that ACC can be activated upon reaching required speed. Three drivers described engaging ACC. No audio-based questions about the system status were provided after the activation cue.

4.3.2. Observations for Normal Event ‘Following Lead Vehicle’

4.3.2.1. Eye Movements group

Following the appearance of the lead vehicle (LV) in the event, four participants detected the LV first, while one detected the LV after first detecting the changes on the IP due to the ACC system detecting an LV ahead. Four participants glanced at the IP after detecting
the LV. After this first initial detection of the LV, all five participants drove ahead while alternating their glances between the IP and the LV on the forward roadway. When the LV pulled over near the end of the event, four changed their lanes after detecting the LV pullover, while one changed their lanes well before the LV pulled over, but none disengaged ACC. When passing the LV, four participants fixated on the LV, while one had a quick glance at the LV.

4.3.2.2. Verbal Response group
All drivers mentioned detecting the LV when it first appeared. Three participants then mentioned that they changed their Set Distance. Two participants described their expectation for ACC’s ability to maintain distance from the LV, i.e., they expected ACC to maintain distance from the LV. Three participants attempted to predict the LV’s speed when following the LV. Four participants described detecting the LV pullover. Three drivers described changing their lanes to pass the LV. One of the drivers described re-engaging ACC after passing the LV which implies that they disengaged it before passing the LV. The audio-based question at the end of the scenario was, “Was the vehicle in front shown on the instrument panel?” Only two participants answered this question correctly.

4.3.3. Observations for Edge-Case Event ‘Traffic Cones’

4.3.3.1. Eye Movements group
All five drivers detected the traffic cones in this scenario. Two participants glanced at least once at the IP after detecting the traffic cones. All five drivers detected the change in speed limit which resulted in three drivers reducing their Set Speed, and two others disengaging ACC. Both the drivers who disengaged ACC, re-engaged ACC towards the end of the scenario.
4.3.3.2. Verbal Response group

Three drivers commented on the change in speed limit, with two drivers also describing lowering their Set Speed. The audio-based question at the end of the scenario was, “Were the traffic cones shown on the instrument panel?”. Four participants answered this question correctly.

4.3.4. Observations for Edge-Case Event ‘Construction Zone’

4.3.4.1. Eye Movements group

All participants detected the construction zone, but only one glanced at their IP after detecting it. All five detected the oncoming car. Three drivers alternated their glances between the oncoming car and the construction zone. When passing the construction zone and the oncoming car, four participants fixated on them. Upon passing, all five glanced at the IP, and two alternated glances between the forward roadway and the IP.

4.3.4.2. Verbal Response group

Four drivers described detecting the construction zone in the scenario. Similarly, four drivers described detecting the oncoming car. Among them, three attempted to predict the oncoming car’s intentions such as giving way to the driver, or waiting till the driver passes. The audio-based question at the end of the scenario was, “Was the Construction zone shown on the instrument panel?”. Four participants answered this question correctly.

4.3.5. Observations for Edge-Case Event ‘Lead Vehicle & Sharp Curve’

4.3.5.1. Eye Movements group

All drivers detected the LV inside the curve, but unlike during the “Following Lead Vehicle” normal event, only two of the Eye Movements group drivers glanced at their IP.
to check if ACC had detected the LV inside the curve. Two drivers disengaged ACC just before or just after entering the curve. While inside the curve, four drivers fixated on the LV or the road ahead with minimal glances at the IP. All drivers detected the LV pulling over at the end of the curved section. Three drivers did not change lanes when passing the LV. While passing the LV, four drivers fixated on the LV. All drivers glanced at their IP after passing the LV.

4.3.5.2. Verbal Response group
All drivers described detecting the LV inside the curve. Three drivers described judging the LV’s driving speed or driving behavior inside the curve. Upon detecting the LV, two drivers expected ACC to detect the LV. Two participants described disengaging ACC during the scenario. The audio-based question at the end of the scenario was, “Did ACC deactivate automatically inside the curve?”. All five participants answered this question correctly.

4.3.6. Observations for Normal Event ‘Divided Freeway Transition’

4.3.6.1 Eye Movements group
All participants changed their Set Speed at the freeway transition, and two re-engaged ACC before doing so (having disengaged in the previous scenario). When changing their Set Speed, two participants fixated exclusively on the IP; while three others made alternative glances between the IP and the roadway. All participants alternated glances between the IP and the roadway in varying degrees after changing their Set Speed.

4.3.6.2. Verbal Response group
Three participants described changing the set speed, among which one explicitly comparing the Set Speed and Vehicle Speed to be of similar value. One driver changed
the Set Distance, while mentioning that this action may prove to be useful later. The audio-based question at the end of the scenario was, “Is your vehicle traveling at your set speed?” All five participants answered this question correctly.

4.3.7. Observations for Edge-Case Event ‘Straddling Lead Vehicle’

4.3.7.1. Eye Movements group
All drivers detected the LV in this scenario. Similar to the “Following Lead Vehicle” scenario, all drivers checked their IP after detecting the LV. Three drivers changed lanes to pass the LV, among which one driver had already disengaged ACC and was driving manually. When passing the LV, four drivers fixated on the LV. Only two drivers glanced at their IP after passing. The driver who disengaged ACC also re-engaged after passing the LV.

4.3.7.2. Verbal Response group
Four drivers described detecting the LV. Three drivers attempted to predict the LV’s vehicle type. One driver expected ACC to slow down when approaching the LV, but later described how ACC failed to do so and failed to maintain the Set Distance from the LV. All drivers attempted to predict the LV’s driving behavior such as reduced speed, pulling over, or both. One driver mentioned disengaging ACC as the LV was pulling over. The audio-based question at the end of the scenario was, “Did ACC deactivate automatically?” All five participants answered this question correctly. The driver who disengaged ACC, re-engaged it at the end of the scenario.
4.3.8. Observations for Edge-Case Event ‘Oversized Lead Vehicle’

4.3.8.1. Eye Movements group

All five drivers detected the oversized LV. Like the previous edge-case event and the “Following Lead Vehicle” normal event, all drivers from the Eye Movements group checked their IP after detecting the oversized LV. One driver disengaged ACC when nearing the LV. All participants passed the LV, where four fixated on the LV when passing and one made alternative glances between the forward road and the LV. Four drivers glanced at their IP after passing the LV. The driver who disengaged ACC, re-engaged after passing the LV, and changed the Set Speed whilst alternating glances between the IP and the road ahead.

4.3.8.2. Verbal Response group

Four drivers described detecting the oversized LV. Three drivers expected ACC to maintain the Set Distance from this LV. Four drivers commented on the LV’s vehicle type. Three drivers described passing the oversized LV. Three drivers described disengaging ACC before passing the LV, with all three later describing re-engaging it towards the end of the scenario. The audio-based question at the end of the scenario was, “Was the oversized vehicle shown on the instrument panel?” Four participants answered this question correctly.

4.3.9. Observations for Edge-Case Event ‘Parked Truck and Lead Vehicle’

4.3.9.1. Eye Movements group

All drivers detected the LV and similar to the other scenarios, all drivers glanced at their IP after detecting it. All drivers followed the LV while alternating glances between the IP and the LV on the forward roadway. All five drivers detected the stopped truck on the
shoulder. Three drivers detected the LV change lanes when the LV passed near the truck. Three drivers fixated on the truck when passing it. All five drivers detected the LV pulling over, and two drivers glanced at their IP after the LV pulled over. One of the drivers disengaged ACC when LV began to pull over. Three participants alternated their glances between the road and the LV when passing the LV, while the other two fixated on the LV. The driver who disengaged ACC, re-engaged after passing LV. All five drivers glanced at the IP at least once after passing the LV.

4.3.9.2. Verbal Response group

All drivers described being aware of the presence of the LV. Four drivers mentioned the presence of the stopped truck on the shoulder, two of which mentioned that the truck was not detected on the IP. Three drivers described detecting the LV pullover, with one of them mentioning how the LV was no longer detected by the IP after pulling over. Two drivers described changing lanes or moving over to pass the LV. One driver described re-engaging ACC after passing the LV, implying that they had disengaged ACC at some point during the scenario. The audio-based question at the end of the scenario was, “Did ACC deactivate automatically near the parked truck?”. All five participants answered this question correctly.

4.4. DISCUSSION ON FINDINGS FROM THE OBSERVATIONAL STUDY

The ability to read one’s driving environment, recognize, and predict oncoming hazards is vital to prevent crashes and collisions. However, while traditional driving has mainly placed environmental elements as precursors for hazards (Pradhan & Crundall, 2017), driving with ADAS and with vehicle automation features in general may present new challenges to the hazard avoidance research domain. The main challenge lies in the gap in
literature regarding driver’s hazard avoidance when driving with ADAS. Moreover, lack of knowledge about ADAS could also result in drivers not recognizing edge-case events (Boelhouwer et al, 2019; Beggiato & Krems, 2013) which could result in crashes or collisions. Therefore, the aim of this sub-study was to observe the eye movements, interactions, and verbal responses of experienced ACC users when driving with ACC in several edge-case events. Ten participants were randomly and equally assigned to two groups – the Eye Movements group and the Verbal Responses group. The former yielded responses based on eye movements and action-based responses to the simulator scenarios, and the latter yielded responses based on verbal commentary and responses to audio-based questions. As a result, the study was able to observe not only the glance-based and action-based behaviors of experienced ACC users in one group, but also observe the awareness about system status and operations and environmental events of similarly experienced ACC users in the other group.

For the Eye Movements group, it was observed that while ACC functioned as intended, i.e., maintaining the selected set speed or set distance, all drivers alternated their glances between the forward roadway and their IP. Similarly, all drivers tend to fixate their gaze on the IP or at least alternate their glances between the IP and the forward roadway when interacting with the ACC system (engaging/disengaging, changing Set Speed, etc.). Out of 25 instances of a lead vehicle appearing in the scenario, there were 21 instances where the drivers checked their IP after detecting them. However, this was not the case when encountering stationary vehicles or objects not directly in their travel path or those which are off-road, where out of 10 instances of a stationary objects (traffic cones and construction zone), there were only 3 glances at the IP after passing
them. Drivers also tend to fixate on the lead vehicle when passing it or at least glance once at it, where out of 25 possible passing events featuring a lead vehicle, there were 23 such instances. Similarly, drivers also tend to check their IP after passing a lead vehicle, with 21 such instances observed. Overall, for this group there were a total of seven disengagements across all scenarios for all five drives.

For the Verbal Responses group, for the eight audio-based questions presented at the end of each scenario, participants answered them with 85% accuracy (34 correct responses out of possible 40). This indicates that these participants were generally aware about the status and changes of the ACC system as presented on their IP. From their verbal commentary, there were nine instances where drivers attempted to predict the LV’s speed or intentions on the roadway such LV pulling over, LV slowing down, etc. Similarly, there were also nine instances where drivers attempted to determine the LV’s vehicle type, size, or shape. There were also nine different instances where the participants expected ACC to detect the LV. However, only in two of those instances would they be correct (both for the “Following Lead Vehicle” event). Also, from the observations it is apparent that 76% of the time, the drivers were aware of the objects and other vehicles on the roadway. This percentage only includes objects or vehicles verbally described by at least one participant. For this group, there was a total of eight disengagements observed across all scenarios for all five drives, bringing the total number of disengagements to 15 across both groups.

The observations from this study could suggest that hazard avoidance when driving with ACC may actually differ when compared to traditional driving due to the increased tendency of drivers to scan their vehicle’s IP when encountering hazards, while
taking the necessary action-based responses to avoid them, and after successfully mitigating them. Their eye movements also make it apparent that they provided somewhat similar attentional resources to both in-vehicle and external elements when driving with ACC. This was seen not only when driving in the edge-case scenarios, but also when driving with normal ACC functions, where drivers alternated their glances between the forward roadway and the instrument panel, which could indicate their intent to keep track or gain continuous real-time information about their surroundings as well as their system’s status. The verbal responses give us further insight into how drivers are aware at least 85% of the time about internal events regarding their system’s status and operations, and 76% of the time about external events and their surroundings. Drivers also appeared to predict and rationalize the reasoning behind events such as those caused by the LV's behavior or by the shape or size of the LV. This is in line with Crundall (2016) who mentioned that prediction plays an important role in successful hazard anticipation (Crundall, 2016). However, also observed were certain mismatches in driver expectations regarding when ACC should detect and maintain distance from LV. Considering that these participants were experienced ACC users, such mismatches may be more prevalent in novice users of ACC. This creates an urgent need to devise appropriate methods to improve not only one’s hazard avoidance when driving with ADAS, but also improve their mental models about ADAS to calibrate their understanding and expectations regarding the systems’ functions and limitations.

4.5. IMPLICATIONS ON DISSERTATION RESEARCH AND NEXT STEPS

The study provides insight into the hazard avoidance behaviors exhibited by experienced users of ACC. These observations can be used to provide some basis for further research.
regarding the differences in hazard avoidance when driving with ADAS compared to traditional driving. These observations also helped to understand drivers’ perceptions and expectations regarding ACC functions and operations. The findings help us better understand the driver’s need for context and information and provide a strong foundation towards research regarding the design and development of training and educational methods to improve the hazard avoidance abilities of novice users and drivers. Finally, the observations from this study also help us to derive specific hazard avoidance related outcome measures for the final experimental evaluation study.
CHAPTER 5.
TRAINING METHODOLOGY - CONCEPT AND DESIGN

This chapter will describe the next phase of research where a training program will be conceptualized and designed to improve drivers’ mental models about Adaptive Cruise Control (ACC) and their hazard avoidance behaviors. The findings from previous chapters and past training studies from literature were utilized in this phase to identify behaviors and responses to prevent hazardous scenarios, that will be featured in the Virtual Reality (VR) headset-based training program.

5.1. ADVANTAGES OF TRAINING

The conceptual framework from Chapter 2 suggests that there is a relationship between drivers’ mental models about vehicle automation and their hazard avoidance abilities. A driver’s mental models about ADAS could be vital for system awareness, given that their mental models will frame their knowledge and expectations of system behaviors. For the same reason, the quality of mental models may also influence the driver’s lookout behaviors. Mental models also influence the driver’s knowledge about how to operate the system at different states and about the correct response actions to change the state of the system. Hence, the quality of mental models may also impact driver responses in terms of system control. Mental models can be influenced by knowledge, experience, system design, and training.

Past research has employed training methodologies to improve driver behaviors such as hazard anticipation (Pradhan et al, 2009; Vlakveld, 2011), hazard mitigation (Muttart et al, 2017), attention maintenance (Pradhan et al, 2011). The advent of ADAS and vehicle automation has also led to research on training programs towards improving
driver performance and interaction with advanced vehicle technologies. Forster et al (2019) tested an interactive tutorial to help drivers understand LKA and found that users of the tutorial had more accurate knowledge when compared to those who receive information from a vehicle owner’s manual (Forster et al, 2019). Noble et al (2019) and Mueller et al (2019) also utilized training methods to improve driver knowledge and driver’s ability to detect state changes for ADAS features (Noble et al, 2019; Mueller et al, 2019). Zahabi et al (2021) tested two training approaches – video-based and demonstration-based approaches to improve older drivers’ trust, knowledge, and mental workload. They found that the former approach was effective for female drivers in reducing mental workload, while the latter approach was beneficial to male drivers (Zahabi et al, 2021).

Literature review revealed several training approaches where some studies have suggested that providing post-hoc or post-drive explanations about takeover control events improved drivers’ knowledge about systems (Körber et al., 2018). It was also reported that post-event feedback improved participants’ safe driving practices when they were informed about takeover situations (Koo et al., 2015). Forster et al (2019) suggested that active and guided tutorials about operating system in form of user quiz led to increased understanding of the systems and better interactions (Forster et al., 2019). Error training is another form of training that has resulted in better transfer of knowledge, i.e., ability to used familiar problems to solve similar problems in the future (Ivancic & Hesketh, 2000). Romoser & Fisher (2009) found that active training (where a user is allowed to interact, make mistakes, and learn) was a more effective strategy than passive learning (lecture type learning with text-based information). Many previous hazard
mitigation and hazard anticipation studies such as the Risk Awareness and Perception Training (RAPT) (Fisher et al., 2002; Pradhan et al., 2009), Anticipate, Control, and Terminate (ACT) (Muttart, 2013), and Engaged Driver Training System (EDTS) (Zafian et al., 2016) have used an active, error-based training approach, sometimes known as the 3M (mistake, mediation, mastery). The 3M approach would be a viable training approach for designing the training program for this research since it is a combination of error-based training and interactive learning techniques which have shown promising results in previous studies.

5.2. REQUIREMENTS FOR DESIGNING A TRAINING PROGRAM

A common aspect among most training programs is that they aim to improve the driver’s mental models regarding the traffic environment to improve their visual scanning behavior towards areas of interest, improve their ability to predict the behavior of other road users, and have an improved situation awareness towards possible hazards in their environment (Horswill, 2016a, 2016b). They also depended on scenarios that elicit legitimate anticipatory behaviors from drivers such as scanning for cues and probable target locations from where hazards may materialize. A training approach for hazard avoidance would also need to include this aspect of improving drivers’ mental models, particularly due to the greater roles mental models play in the context of ADAS usage. As mentioned in previous chapters, it is paramount for drivers to possess a complete and accurate mental model about their system’s functionalities and limitations, and hence improving their mental models can lead to improvement in their abilities to avoid hazards and remain situationally aware even when they are not actively in the control loop.
It may also be of interest to choose the right mode of delivery of the training since all training platforms do not produce the same results in terms of efficacy and learning. It may be prudent to choose a platform that can implement an interactive and error-based training approach that has been shown to be effective in training drivers to learn and retain important driving skills (Forster et al., 2019; Ivancic & Hesketh, 2000; Pradhan et al., 2005; Romoser & Fisher, 2009). A recent study made use of a state diagram visualization of ACC as training material and compared it to an owner’s manual in terms of impact of user knowledge about ACC. The results found a significant increase in knowledge about ACC after training. It was also found trained drivers had better real-time awareness of the system states than the control group that did not receive meaningful training (Pradhan et al, 2022). When comparing a limitation-focused training approach to a responsibility-focused training approach, it was found that there were no differences between the two approaches regarding the drivers’ knowledge related to ADAS (DeGuzman & Donmez, 2022).

Interactive training methods such as video-based training and VR headset-based training have also been utilized in past studies. Video-based training has been utilized by several training studies in the past to improve driver knowledge and workload (Zahabi et al., 2021) and hazard perception (Isler et al., 2009). Virtual reality headsets (VR) are powerful educational tools and have already been employed in hazard anticipation training studies for manual driving (Bozkir et al., 2019; Madigan & Romano, 2020). VR headsets offer an immersive learning experience and have been making strides in the field of education (Elmqaddem, 2019; Velev & Zlateva, 2017). Past research has indicated that
VR-headsets can measure driver behaviors such as hazard anticipation and can serve as an effective tool for driving simulation (Pai Mangalore et al., 2019; Silvera et al., 2022).

5.3. TRAINING CONCEPTUALIZATION AND DEVELOPMENT

5.3.1. Chosen Modes of Delivery

5.3.1.1. Virtual Reality Headsets

Virtual Reality (VR) headset was chosen as the primary mode of delivery for the newly developed training program based on recommendations from past studies (Silvera et al., 2022; Madigan & Romano, 2020; Bozkir et al., 2019) towards the usage of VR in simulating driving environments and developing driver training. The training content designed for the VR headset would consist of both static and dynamic informational modules, derived from past training research (Pradhan et al., 2022a; 2022b) as well as a quiz component after completion of each training module to implement an error-based training approach (Ivancic and Hesketh, 2000). More information about the VR headset used to deliver the training is provided in section 5.5.

5.3.1.2. State Diagram Training

The State Diagram (SD) visualization training program designed by researchers at the Human Performance Laboratory in the University of Massachusetts Amherst was chosen as one of the modes of delivery for training. This training method is based on prior work on advanced vehicle technologies (Pradhan et al., 2020; Pradhan et al., 2021) and includes streamlined content from vehicle owner’s manual along with visual representation of an ACC system in the form of a state diagram. Other information such as the limitations of ACC were also included in the training.
It is important to note that the SD training program was not developed during this dissertation research. However, it was partially modified and segmented similar to the newly designed VR training for future evaluation purposes. Also, similar to the VR training, the SD training also featured a quiz after completing each training module. More information about the State Diagram method will be provided in the next chapter.

5.3.2. Module Descriptions

The content presented in the training was presented in form of separate modules that tackled various topics about the functions and limitations of ACC and have been listed below. Both the VR and SD training methods featured content based on the below modules in the program. More in-depth contents of the modules will be described in section 5.5.

5.3.2.1 ACC Overview and Basics

The first module provided an overview of ACC. The role of ADAS and ACC in contrast to traditional driving as well as the basic functions and limitations of ACC were mentioned in this module.

5.3.2.2 ACC Controls & Display

The second module presented information about ACC states, controls, and display icons on the instrument panel. This module would help the user understand how ACC states can be changed using the various buttons and mechanisms available inside the vehicle. By providing information of the various display icons represented on the instrument panel, this module would also equip the user with knowledge and awareness about their system’s status by obtaining information from the instrument panel.
5.3.2.3. *ACC Limitations*

This module presented information about ACC limitations gathered from vehicle owner’s manual of various ACC systems (Toyota, Subaru, etc.). This was the third and final module presented in the SD training, whereas in the VR training this module was presented as the fourth module. Users would obtain information about situations where the ACC system may not function properly or malfunction, and hence be better prepared to assume manual control of their vehicle in such events.

5.3.3. *Additional Modules in the VR Training Program*

To leverage the graphical and immersive capabilities offered by VR headsets, two additional modules were designed for the VR training. These modules provided a real-time representation of ACC functions and operations under different conditions.

5.3.3.1. *Real-Time ACC Functions*

The third module for the VR training showed ACC functioning in real-time. Users would experience a short, scripted instance of ACC functioning while seated in the driver’s seat. Visuals showed ACC performing different functions, accompanied by on-screen text and voice-overs.

5.3.3.2 *ACC Edge-Case Events*

The fifth and final module for the VR training presented two edge-case events where ACC would not function properly. Findings from the earlier observation study were utilized to inform the user about the relevant areas to be scanned both internally and externally and recommend actions to be performed to avoid oncoming hazards.
5.4. APPARATUS & APPLICATIONS

5.4.1. Unity

The Unity game engine is a powerful, versatile game engine extensively used for developing VR applications. It provides developers with a broad set of tools to create immersive VR applications and gaming experiences. Unity supports various VR platforms, such as Oculus Rift, HTC Vive, etc., allowing developers to build applications with cross-platform functionality. Unity also enables the developers to rapidly build and test applications by providing previews (through a feature called “Game” view), without the requirement of physical hardware, which is valuable in the iterative design process. It is also versatile in terms of the programming languages used, since both C# and JavaScript scripting are compatible with Unity, allowing a wider range of developers to make use of its capabilities. In this study, the unity game engine was used to design and develop both the training content as well as high-quality visual environments with different roadway sections for the individual modules and virtual classrooms for the quiz sections, to fully immerse the user in their training application (Figure 5).

![Figure 5. Immersive Virtual Environments in Unity](image_url)
5.4.2. HTC Vive ProEye

The HTC Vive ProEye (Figure 6) is an advanced virtual reality headset designed for immersive experiences and applications. Similar to the original HTC Vive Pro, the HTC Vive ProEye features dual OLED displays with a combined resolution of 2880 x 1600 pixels and a refresh rate of 90Hz, providing the user with a 110-degree field of view. However, unlike the original Vive Pro, this headset has integrated eye-tracking technology by Tobii which enables monitoring eye movements within virtual environments by accurately capturing where users are looking and enabling features like foveated rendering, which focuses graphical processing power on the area of the screen where the user's eyes are fixated, thus optimizing performance and visual quality. The headset consists of two handheld controllers to help with user interactions and has built-in headphones with 3D spatial audio support. The headset features an adjustable head strap and ergonomically designed face cushion for comfort during extended use. The design of this headset is ideal for use by researchers for developing training programs and simulation applications.

Figure 6. HTC Vive ProEye
5.4.3. Qualtrics

The training content for the SD training method was developed on Qualtrics. The training program was designed to be presented to the user through an Apple iPad. The training program would be presented in the order of the modules discussed earlier and each module would be accompanied by a quiz after completion of each module to implement the error-based training approach (Ivancic and Hesketh, 2000).

5.5. TRAINING MODULE CONTENT & DESIGN

There were some inherent similarities between the training content and design presented in the SD and VR training programs. Both training programs are user-centered and self-guided, which means the user has more control over the pacing and flow of information presented in the training. Upon completion of each module, both training programs featured a quiz where they were asked six questions based on the content presented in the completed module. The quizzes were included to implement the error-based training approach (Ivancic and Hesketh, 2000). The questions for each individual module were brainstormed and updated during each iteration of the development process. The users would not be able to proceed with the training unless they completed the quiz and were able to answer four out of the six questions correctly. This threshold was selected to permit only those users that could answer more than 50% of the questions correctly to proceed to the next training module. In a case where the user was unable to answer four questions correctly (answered only 50% of the questions or less correctly), they would be redirected to the previous module to view the training material once again, after which the quiz would be presented for one more attempt. The same set of questions were
presented in quizzes for the common modules (ACC Overview and Basics, ACC Controls & Display, and ACC Limitations) for both training programs.

The VR training was designed to be a highly immersive experience with the user seated in the driver’s seat in the virtual cab within the virtual environment with full view of the steering wheel, buttons, instrument panel, and the forward road ahead. Textual information was projected onto a virtual canvas in the user’s forward field of view, which also featured the user interface (UI) to control the pacing and flow of the training. The user would make use of a handheld VR controller to control and click on different UI elements. The virtual world was also accompanied by annotations and highlighted icons to help the user find the buttons, and display icons. Audio voice-overs were also provided to accompany the textual information, and the UI enabled the user to replay the voice-over if needed. The user was then seated in a virtual classroom upon completion of each training module, where they would be able to answer the quiz questions using a handheld controller.
5.5.1. ACC Overview and Basics

Figure 7. Opening Section of the Training Program

This was the opening module and contained instructions on how to navigate and use the training program. At the very start of the training, the user was allowed to adjust their seating position and test their handheld controller (Figure 7). They were then shown the main learning objective of the module both visually and verbally through audio voice-overs, i.e., to learn about the basics of ACC. The module described driving as a complex task and how ADAS features were designed to assist drivers in handling vehicle control tasks. The user was then introduced to ACC and its functions, i.e., speed and gap distance control (Figure 8). The user was also informed about how and when ACC could be operated, and then shown some quick examples where ACC may not work properly.
At the end of the module, the user was shown an end screen which informed them that they would need to press the ‘finish’ button to be teleported to a virtual classroom to answer the quiz for this module. The quiz can be seen in Figure 9 where the left image shows the question presented to the user along with the answer options, and the right image showing the visuals when the user answers the question correctly. As per the quiz rules, the user would need to answer at least four of the six questions correctly to proceed to the next module or re-do the current module and attempt the quiz once again.
5.5.2. ACC Controls & Display

The main objective of this module was to familiarize the user with the controls of ACC and the display icons on the instrument panel (Figure 10). The various different states/modes of ACC were mentioned on the virtual canvas.

Figure 9. Example question from the quiz (left image); Screen displayed for answering the question correctly (right image)

Figure 10. ACC Controls & Display Module
The environment around the user and their virtual cab would also change dynamically whenever ACC mode changed. However, unlike the next module, the information was segmented and not presented in one continuous animation, so that the user had the freedom to properly familiarize themselves with the display icons and highlighted buttons required to transition from one ACC mode to another (Figure 11). The module also featured ‘recap’ of information learned where the user would be given a quick recap of the new control and display icons functionalities they just learned (Figure 12).

Figure 11. Example for highlighted buttons (left image); Example for highlighted display icon on the instrument panel (right image)
6.5.3. Real-Time ACC Functions

This VR exclusive module was presented next and served as a real-time demo of ACC with a scripted animation showing the user all the functions and display states of ACC icons in a dynamic moving vehicle on a roadway with varying speed limits and a lead vehicle. The scripted scenario would begin with the virtual cab starting from rest and slowly gaining speed while ACC is not switched on. The scenario then proceeds to show the user how ACC switches on (Figure 5.9), what conditions need to be fulfilled to activate its functions, how the set speed can be changed (Figure 13), and how the system
reacts when it detects a lead vehicle in front (Figure 14). Similar to previous modules, this module would transport the user to the virtual classroom in order to answer the quiz.

Figure 13. ACC switches on (left image); ACC activating (right image)

Figure 14. Changing Set Speed (left image); Changing Set Distance (right image)

5.5.4. ACC Limitations

In the fourth module presented to the user, they were informed about the various limitations of ACC. Here, some dynamic situations where ACC does not function properly were shown to the user. The user was also given a quick recap of instances shown in the first module, where ACC does not function properly. A total of five such situations were shown to the user and some examples have been shown in Figure 15. This module was similar in terms of textual content to the third module of the SD training program and the quiz also consisted of the same questions and answers. In another
example, the screen displayed when the user answers the question incorrectly is shown in Figure 16.

![Example question from the quiz (left image); Screen displayed for answering the question incorrectly (right image)](image)

Figure 15. Examples of ACC Limitations Situations

![Wrong answer](image)

Figure 16. Example question from the quiz (left image); Screen displayed for answering the question incorrectly (right image)

5.5.5. ACC Edge-Case Events

The fifth and final module for the VR training was the “ACC Edge-Case Events” module which was also exclusively developed for the VR training. This training was developed as a result of the findings from the observational study which emphasized the importance of drivers’ system awareness, and their glance activity towards external and internal elements that may be detrimental to the system’s optimal functioning and operational. The module first explained to the users that the term “Edge Case” meant those events on
the roadway that occur outside ACC’s normal operating conditions, resulting in hazardous conditions where ACC may not function properly or fail altogether (Figure 17).

Figure 17. The meaning of the term ‘Edge Case’
(as described in training module)

Next, the user was informed that the next portion will feature a dynamic scene with a hazardous scenario. In this scenario, the user’s cab would follow a lead vehicle (LV) in the right lane (Figure 18). The Set Distance is set to the ‘short’ setting, and the cab follows the lead vehicle closely, and is hence travelling at a speed slower than the Set Speed of the vehicle. After following the LV for a few seconds, the LV moves over to the left lane, due to a stopped oversized truck in the right lane. This causes ACC to revert to the original set speed of 65 MPH, since ACC does not detect stationary or oversized vehicles.
Figure 18. First edge-case event presented in the “ACC Edge-Case Events” module. The user’s cab would come to a full stop close to the stopped truck, just in time to prevent a collision, after which the frames would freeze and the user would be explained about what took place in the event, as explained earlier. The user would be given an explanation about the factors that caused this event to occur: 1) the cab was following the LV below the set speed; 2) the LV changed lanes and ACC reverted to the Set Speed; 3) ACC did not detect the truck. (Figure 19)

Figure 19. Factors that caused the scenario to occur (as described in training module)
Next, the user would be informed about the right set of behaviors or actions that they could have adopted during the scenario that would have prevented it from occurring. First, it was important to be aware of one’s surroundings, where a driver would need to be aware of the changes occurring in their driving environment, such as actions of other road users and also be on the lookout for stationary vehicles or objects in their path. Second, drivers would need to continuously monitor the status of the system for any state changes occurring due to on-road events. For instance, in the above scenario, when the LV changes lanes, the instrument panel also corresponds to this change, showing that ACC is no longer detecting the LV (Figure 20). Last, the driver would need to be always ready to assume manual control of their vehicle, since ACC does not possess the ability to react in such scenarios.

Figure 20. Recommended Actions for preventing hazardous situations (as seen in training module)
This would be followed by another scenario where the user’s cab is travelling at the Set Speed and encounters a slow-moving uniquely shaped lead vehicle and fails to detect it. Similar explanations and recommended actions as the first scenario were then shown to the user. At the end of this module, the participant would receive a quiz with slightly different conditions. In this quiz, the participants would be given two scenarios at different points in the quiz, with three questions each related to the scenarios (Figure 21). The user would still need to answer any four out of the six questions in the quiz correctly to finish the training program.

Figure 21. Quiz for the “ACC Edge-Case Events” module

5.6. IMPLICATION ON DISSERTATION RESEARCH AND NEXT STEPS

This phase of research resulted in a newly designed training program that leveraged the immersion and graphical capabilities of VR headsets to deliver an exciting new approach to training that informs the users about not only the basics of ACC, but gives them a comprehensive tutorial about the various control mechanisms, display icons, and system states of ACC. Moreover, the training exposes the users to instances where ACC does not work properly or fail, and also informs them about the necessary responses and actions to undertake in order to maintain their safety when driving with ACC. The efficacy of this training program has been evaluated in an experimental study detailed in the next chapter.
CHAPTER 6.

EVALUATION OF TRAINING METHOD

This chapter explains the methodologies, experimental design, procedure, and analyses techniques used to carry out an experimental evaluation study on a driving simulator to test the efficacy of the newly designed training program from the previous chapter in improving driver’s mental models about ACC and their hazard avoidance when driving with ACC. The main objective of this evaluation study is to test and examine the hypotheses proposed for this dissertation research and answer the research questions posed at the beginning of the research. This research phase is the culmination of this dissertation research and makes use of the insights and findings gathered from all previous phases. In a mixed-subject design, 36 participants were recruited for this evaluation study and assigned to one of three training groups. Their mental models were measured both before and after training, and a simulator drive with various edge-case events was used to examine their hazard avoidance behaviors. The study provides some interesting details about the effect of training and training platform on driver’s knowledge and interactions with ACC. The results gives us invaluable insights into the relationship between training, mental models, and hazard avoidance and bridges a major gap in literature about hazard avoidance in the context of vehicle automation. This may be crucial when considering how widespread the use of ADAS has become, and the rapid advancement towards higher levels of vehicle automation. Hence the findings from this evaluation study may have important implications in the human factors in transportation and vehicle automation domain.
6.1. STUDY OBJECTIVES AND HYPOTHESES

The aim of this final research phase is to evaluate if training improves drivers’ mental models and hazard avoidance and understand the impact of different training platforms. The overall goal of this dissertation research was to answer the following research questions,

1. How does hazard avoidance differ when driving with ADAS?
2. How can training be designed to improve mental models, in terms of content & delivery method (platform)?
3. Does improved quality of mental models through training lead to improvements in the drivers’ hazard avoidance behaviors?

In Chapter 3, after proposing the conceptual framework for Hazard Avoidance in the vehicle automation context, the following hypotheses were generated to be tested and examined in this research phase.

H1. Training impacts the drivers’ mental models about ADAS
H2. The Training platform has an impact on the driver’s mental model
H3. Training affects driver’s mental model which in turn affects their System Awareness
H4. Training affects driver’s mental model which in turn affects their Lookout Behaviors
H5. Training affects driver’s mental model which in turn affects their System Control skills

6.2. METHODS

6.2.1. Participants

A total of 36 participants aged between 18 to 65 years (mean = 23.92; SD = 8.47) from the Amherst area in Western Massachusetts were recruited for this study. A power
analysis revealed that the selected sample size had power \((1-\beta)\) of 0.87. Participants were also required to have a valid United States driver’s license. Further, the participants were also required to be able to read and write in English to be able to appropriately participate in the study when interacting with the training materials, questionnaires, and simulator drive. The participants’ familiarity and experience using ACC were established by using a screening survey prior to study participation and only those participants who self-reported to having little to no experience using ACC were included in the study. Institutional Review Board approval was also sought and granted for conducting the study.

### 6.2.2. Equipment & Apparatus

#### 6.2.2.1. RTI Fixed-Base Driving Simulator

The RTI Driving Simulator in the UMass Human Performance Lab, used in the earlier observational study, was also used for this study (Figure 22). The simulator has a built-in engine known as ‘SimCreator’ and the SimADAS package within SimCreator equips the simulator with several ADAS functionalities. This study makes use of the ACC feature of SimADAS which maintains the vehicle’s speed and gap distance from a lead vehicle and possesses the functionalities and limitations of real-world ACC systems. A more in-depth description of the RTI Driving Simulator can be found in section 4.2.2. in Chapter 4.
Figure 22. RTI Fixed-Base Driving Simulator

6.2.2.2. *Tobii Pro Glasses 3*

The Tobii Pro Glasses 3 (Figure 23) is an eye-tracking device that of 16 infrared illuminators and four eye cameras integrated into the glasses and makes use of corneal reflection, dark pupil, and stereo geometry techniques to adeptly track the wearer’s eye movements and gaze points with $0.6^\circ$ accuracy and sampling rate of 50 or 100 Hz. The device uses a one-point calibration procedure where a calibration card, featuring a thick black circle, is placed 0.5m to 1m away from the eye tracker and parallel to the wearer’s head forward head position. It also has a scene recording camera which captures a real-time video feed with $106^\circ$ field of view from the wearer’s point of view. The device also synchronizes the eye-tracking metrics with the recorded video output, which can be further processed using a software known as Tobii Pro Lab to include a video output overlaid eye-tracking cursors and scanning path visualizations.
6.2.2.3. HTC Vive ProEye & Unity

The HTC Vive ProEye (Figure 24) is a VR headset that features dual OLED displays with a combined resolution of 2880 x 1600 pixels and a refresh rate of 90Hz, providing a 110-degree field of view. This headset also has integrated eye-tracking technology by Tobii and consists of two handheld controllers, and built-in headphones. Unity is a powerful gaming engine that has been used to develop and test applications for VR headsets. Unity has an in-built preview feature (called “Game” view), which was used to deliver the training in real-time through the HTC Vive ProEye, giving the handling instructor a real-time video feed of the participants’ point of view in the virtual world. More information about Unity and the HTC Vive ProEye can be found in section 5.4.1. and section 5.4.2. in Chapter 5, respectively.
6.2.3. Experimental Design

6.2.3.1. Independent Variables

The experimental design for the study was a mixed-subject design, with training group as the between-subject variable, and event type as the within-subject variable. Event type is the category of events included in the simulator drive. A total of eight events (Table 3) were featured in the simulator drive as scenarios among which six were classified as ‘edge-case’ events (EE) and two as ‘normal’ events (NE). As mentioned in Chapter 4, ‘edge-case’ events are those driving situations where ACC cannot operate appropriately due to the system having reached its ODD limits, and ‘normal’ events are those driving situations where ACC is expected to operate appropriately as intended. These events have been briefly described in this section again and can be seen in Table 3.
Table 3. Description of scenario events in the simulator drive and their event types

<table>
<thead>
<tr>
<th>Order</th>
<th>Event Name</th>
<th>Event Type</th>
<th>Event Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Following Lead Vehicle</td>
<td>NE</td>
<td>The driver approaches an LV on a divided freeway (speed limit – 65 mph) and ACC maintains the desired Set Distance from it</td>
</tr>
<tr>
<td>2</td>
<td>Traffic Cones</td>
<td>EE</td>
<td>The driver approaches a transitional area to an undivided roadway with decreased speed limit (50 mph) and traffic cones on the shoulder</td>
</tr>
<tr>
<td>3</td>
<td>Construction Zone</td>
<td>EE</td>
<td>The driver approaches a construction zone on the opposite side of the road where an oncoming car also approaches the construction zone</td>
</tr>
<tr>
<td>4</td>
<td>LV &amp; Sharp Curve</td>
<td>EE</td>
<td>The driver encounters an LV when travelling inside a sharp curved roadway section</td>
</tr>
<tr>
<td>5</td>
<td>Divided Freeway Transition</td>
<td>NE</td>
<td>The driver enters a transitional area where the undivided roadway changes to a divided freeway with increased speed limit (65 mph)</td>
</tr>
<tr>
<td>6</td>
<td>Straddling LV</td>
<td>EE</td>
<td>The driver encounters an LV that is straddling the lane lines</td>
</tr>
<tr>
<td>7</td>
<td>Oversized LV</td>
<td>EE</td>
<td>The driver encounters an oversized, slow-moving LV</td>
</tr>
<tr>
<td>8</td>
<td>Parked Truck &amp; LV</td>
<td>EE</td>
<td>The driver approaches an LV and ACC initially maintains the desired Set Distance from it. However, the lead vehicle suddenly swerves onto the left lane upon reaching a parked truck on the shoulder.</td>
</tr>
</tbody>
</table>

All participants were randomly and equally assigned to one of three Training groups: Virtual Reality Headset-based training group (VR), State Diagram visualization training group (SD), or Basic Information group (BI). These groups along with their training content have been briefly described below.
6.2.3.1.1. Virtual Reality Headset-based training (VR) group

The Virtual Reality Headset-based training group received the newly designed training program developed during the research described in Chapter 5, through a virtual reality headset (Figure 6.3). To summarize, the VR training features five training modules, three of which are common with the other groups ("ACC Overview and Basics", "ACC Controls and Display", and "ACC Limitations"), and two more which were exclusively developed for the VR training ("Real-Time ACC Functions" and "ACC Edge-Case Events"). A quiz was featured at the end of each training module and the participants had to have answered at least four out of six questions correctly in order to progress to the next training module. The quiz questions for the common training modules were similar across all groups. The modules and contents of the VR training have been explained in detail in Chapter 5 in section 5.5.

6.2.3.1.2. State Diagram visualization Training (SD) group

The State Diagram visualization training program was designed by researchers at the Human Performance Laboratory in the University of Massachusetts Amherst based on prior work on AVTs (Pradhan et al, 2020; Pradhan et al, 2021). The training method included streamlined and simplified information about ACC as derived from vehicle owner’s manuals, along with a state diagram visualization of ACC functions and states (Figure 25). The state diagram represented all possible states of ACC as circles, and the arrow connectors between the circles represented state transitions along with the conditions required to achieve those transitions though means such as buttons presses. Other information such as the limitations of ACC were also included in the training. The training content was segmented into three modules ("ACC Overview and Basics", "ACC
Controls and Display”, and “ACC Limitations”), similar to the VR training content. The SD training also featured the same quiz featured at the end of the VR training modules, and also follow the same rules for progressing through modules.

Figure 25. State diagram visualization of ACC (included in the SD training material developed by Pradhan et al (2022a, 2022b))
6.2.3.1.3. Basic Information (BI) group

The Basic Information group included generic text-based information and descriptions of ACC functions and limitations. The content for this group’s informational material was derived from real-world vehicle owner’s manuals. The participants in this group were meant to receive only basic information about ACC along with a list of limitations, similar to how a new vehicle owner receives information about their ACC system from their owner’s manual (McDonald et al., 2018). However, the information derived from numerous owner’s manual was curated and streamlined to be easy to understand and to minimize the time spent in searching for ACC relevant content from an actual owner’s manual. The material was also segmented into three different modules as seen in the SD and VR groups and had a quiz component to maintain consist of practices throughout the study’s procedures. This group would serve as the baseline since it is apparent from literature that many new users of ACC usually seek information about their system from the owner’s manual (McDonald et al, 2018; Jenness et al, 2008).

6.2.3.2. Dependent Variables

The dependent variables included in this study have been listed below.

6.2.3.2.1. Mental Model Survey Scores

A mental model survey developed by Pradhan et al (2022) was used for measuring the participants’ knowledge about ACC. The survey evaluated the participants’ familiarity with ACC functions, operations, and limitations. The survey has a total of 74 items which were categorized as ‘general knowledge’ items, which focused on general knowledge about ACC and its functionalities, and as ‘specific knowledge’ items, which focused on more nuanced knowledge about ACC system functions such as parameters and conditions
required for change of ACC state or change within a particular ACC state. Each of the
general knowledge (GMM) items included true or false statements regarding the various
functions, limitations, and aspects of the ACC system and the participants could either
agree or disagree with the statements on a 6-point scale. The six-point scale (from
strongly agree to strongly disagree) was based on a confidence-based assessment
approach, and the response on the 6-point scale indicated both the accuracy of one’s
response, and the confidence they had in that response. If the participants’ response to the
GMM item was correct, they would be presented with the corresponding specific
knowledge or SMM items. There was a total of 24 GMM items and 50 SMM items.
During the analyses, the participants’ responses on the 6-point scale would be translated
to a scale of 0 to 100 for the correctness of their response, considering the reversal of
answers for the false scale, for both the GMM and SMM items yielding two mental
model survey scores, the *GMM score* and the *SMM score* respectively.

6.2.3.2.2. ACC Interactions

ACC interactions were derived from the simulator output of the count of button presses
made by the participants during their drives. For the purposes of this study, only those
button presses that resulted in a state change of the ACC systems’ activation were
included. Applying the brakes was also considered as a ‘button press’ since braking lead
to deactivation of ACC. This refers to any instance where a button press led to activation,
deactivation, or reactivation of ACC during the drive. Additionally, interactions which
caused ACC states to change from ‘Speed Control’ (i.e., when ACC is controlling the
vehicle’s speed according to the driver’s selected Set Speed) to ‘Distance Control’ (i.e.,
when ACC is controlling the vehicle’s speed according to the driver’s selected Set
Distance), or vice versa were also considered. The dependent measures derived from the button-press counts were categorized into *engaged interactions* and *disengaged interactions*. Engaged interactions were derived from the sum of counts of button presses which leads to ACC active states (activation, reactivation, switched on, Speed Control to Distance Control, or Distance Control to Speed Control) during the simulator drive. These would typically be the total sum of counts of button presses for the SetPlus, SetMinus, Distance, and Resume buttons. Disengaged interactions were the total sum of counts of button presses which leads to ACC inactive states (deactivation and switched off) during the simulator drive. These would typically be the total sum of counts of button presses for the Cancel, and ACC Off buttons, and braking.

### 6.2.3.2.3. External Glances Score

The *External Glance Score* was the mean score of the two required external glances during each event during the drive and were derived from the participants’ eye movements. The two required external glances were the external detection glance and the external assessment glance. The external detection glance was a binary-coded glance response for detection of the ‘target zone’ (hazard element in each scenario event) within a ‘launch zone’ whose start point was placed approximately 100 meters before the start of a scenario and whose end point was placed right before the audio-based probe at the end of each event. The external assessment glance was another binary-coded glance response for a glance placed on the target zone when passing near it in each event. Participants would receive a score of 0 or 100 for each of the binary-coded glances, and the external glances score would be the mean score of the two scores.
6.2.3.2.4. Internal Glances Score

The Internal Glance Score was the mean score of the two required internal glances during each event during the drive and were derived from the participants’ eye movements. The two required internal glances were the internal detection glance and the internal assessment glance. The internal detection glance was a binary-coded glance response for a glance placed on the instrument panel after detection of the ‘target zone’ during each scenario event. The internal assessment glance was another binary-coded glance response for a glance placed on the instrument panel after the participant has passed the target zone. Participants would receive a score of 0 or 100 for each of the binary-coded glances, and the internal glances score would be the mean score of the two scores.

6.2.3.2.5. System Awareness Score

The System Awareness Score was derived from the participants’ verbal responses to the audio probes received after each event. Each probe was a simple ‘yes’ or ‘no’ question about the ACC system’s status and was placed right at the end of each event. The probe questions have been provided in the appendix. Correct responses received a score of 100, while incorrect responses received a score of 0. This score was used to measure the System Awareness component in the Hazard Avoidance framework from Chapter 3.

6.2.3.2.6. Response Accuracy Score

The Response Accuracy Score was derived from assessment of the participants’ action-based responses to the scenarios during each event. The correct and incorrect responses were predetermined for each event. If participants performed the ‘correct’ set of actions during an would receive a score of 100, while the ‘incorrect’ set of actions would result in
a score of 0. This score was used to measure the System Control component in the Hazard Avoidance framework from Chapter 3.

6.2.4. Experimental Procedure

Prior to their visit to the lab, the participants were randomly assigned to a training group. After arriving at the lab, the participants provided their informed consent for participation in the study. They then filled out a demographics questionnaire which collected basic demographics and driving experience information. They were then directed to complete the Mental Models survey, before being introduced to their assigned training method. The training process lasted for approximately 30 minutes, although the participants were given independence to control the pacing and flow of the training. After the completion of the training, they were once again directed to complete the Mental Models survey.

Before the main simulator drive, the participants were allowed to drive through a short practice drive on the simulator that would last no longer than five minutes. During the practice drive, the participants were familiarized with the controls of the simulator cab and its ACC system and were also given an opportunity to adapt themselves to the virtual world and audio cues provided by the simulator. The participants were then presented with the main simulator drive (described in Table 3). At the beginning of the drive, an ACC activation audio cue – “Remember to activate Adaptive Cruise Control”, was provided to the participants to prompt ACC usage, and throughout the drive they also received navigational audio cues (such as lane change cues) during the drive. Following the completion of the drive, the participants were paid $40 as compensation for their participation in the study. Each participant’s visit would last for no more than 90 minutes including the training session, time taken to fill out surveys, and the simulator drive.
6.2.5. Analyses

To analyze the GMM and SMM scores, a 2 x 2 factorial ANOVA was used were the Training Group (BI group, SD group, and VR group) and Condition (Pre-Training vs Post-Training conditions). For all other analysis, generalized linear models were used to analyze the associations between the independent variables (Training Group and Event Type) and the other dependent variables mentioned earlier in Section 6.2.3.2. Interaction effects, unless significant, were weaned out from the models, and the significance level was set to 0.05.

6.3. RESULTS

6.3.1. Mental Model Scores

6.3.1.1. GMM Score

Analyses revealed that there was a main effect of training group on the participants’ GMM scores (F = 3.48; p-value = 0.036). There was also a main effect of condition on the GMM scores (F = 73.12; p-value < 0.001). Post hoc tests revealed that there were significant differences between the GMM scores of the SD group and BI group, with SD group (82.26) having higher scores than the BI group (76.04). The VR group (78.37) also had higher scores than BI group (76.04), although it was not statistically significant. Participants’ post-training GMM scores (87.2) were found to be higher than their pre-training GMM scores (70.58) (Figure 26).
6.3.1.2. SMM Score

Analyses revealed that there was no main effect of training group on the participants’ SMM scores ($F = 2.094; p$-value = 0.131), although a main effect of condition on the SMM scores ($F = 81.835; p$-value < 0.001) was found. Participants’ post-training SMM scores (80.45) were found to be higher than their pre-training SMM scores (64.84) (Figure 27).
6.3.2. ACC Interactions

6.3.2.1. Engaged Interactions

Analyses revealed that there was a main effect of Event Type ($\chi^2 (1, N = 36) = 37.68, p < 0.001$) on the total count of engaged interactions carried out by participants, where the interactions were higher for the EE events (81) when compared to the NE events (21). However, there was no main effect of Training Group ($\chi^2 (2, N = 36) = 2.13, p = 0.34$) for the same. (Figure 28)
6.3.2.2. Disengaged Interactions

Analyses revealed that there was a main effect of Event Type ($\chi^2 (1, N = 36) = 59.68, p < 0.001$) on the total count of disengaged interactions carried out by participants, where the interactions were higher for the EE events (78) when compared to the NE events (10). However, there was no main effect of Training Group ($\chi^2 (2, N = 36) = 1.57, p = 0.46$) for the same. (Figure 29)
6.3.3. External Glances

Figure 30. Mean External Glances Scores during each event type for across all three groups
Analyses revealed that there was a main effect of Event Type ($\chi^2 (1, N = 36) = 4.6, p = 0.031$) on the participants’ mean external glances scores, where the mean scores were higher for the NE events (98.61) when compared to the EE events (94.21). However, there was no main effect of Training Group ($\chi^2 (2, N = 36) = 2.983, p = 0.224$) for the same. Overall, the VR group (96.875) had higher scores than both the BI group (95.833) and SD group (93.229), although this difference was not statistically different (Figure 30).

There was also no main effect of Training Group found when analyzing external glances scores considered only for the EE events ($\chi^2 (2, N = 36) = 4.341, p = 0.1141$). The VR group (96.53) had higher External Glances scores than the BI group (95.14) and SD group (90.97), although not statistically significant. When considering for only the NE events, the SD group scored a perfect mean external glances score of 100 and had higher External Glances scores than the BI group and VR group who had the same score.
97.92, although these differences were not statistically significant ($\chi^2 (2, N = 36) = 1, p = 0.6065$).

A Pearson’s product-moment correlation test (Figure 31) was conducted to examine the correlation between the participants’ post-training mental scores (both GMM and SMM scores) and the External Glance scores across all three groups. The correlation tests revealed no significant correlations between the post-training GMM scores and the external glances scores ($r (34) = 0.011; p = 0.95$) or between the post-training SMM scores and the external glances scores ($r (34) = -0.17; p = 0.32$).

![Figure 31. Correlations between the External Glances Scores and the Mental Model Scores](image)
6.3.4. Internal Glances

![Graph showing mean internal glances scores for each event type and training group.]

Figure 32. Mean Internal Glances Scores during each event type for across all three groups

Analyses revealed that there was a main effect of Event Type ($\chi^2 (1, N = 36) = 44.144$, $p > 0.001$) on the participants’ mean internal glances scores, where the mean scores were higher for the EE events (89.12) when compared to the NE events (62.5). However, there was no main effect of Training Group ($\chi^2 (2, N = 36) = 4.341$, $p = 0.0747$) for the same. Overall, the VR group (86.46) had higher scores than both the BI group (77.08) and SD group (83.85), although this difference was not statistically different (Figure 32).

On further analyses, there was a main effect of Training Group on the Internal Glances Scores ($\chi^2 (2, N = 36) = 9.416$, $p = 0.009$) when considering only for EE events. Post hoc analysis revealed that the VR group (94.445) had significantly higher scores than the BI group (82.639) and the SD group (90.278). However, no such effect of Training Group was found when doing the same for only the NE events ($\chi^2 (2, N = 36) = 0.111$, $p = 0.9456$).
A Pearson’s product-moment correlation test (Figure 33) was conducted to examine the correlation between the participants’ post-training mental scores (both GMM and SMM scores) and the Internal Glance scores across all three groups. The correlation tests revealed no significant correlations between the post-training GMM scores and the internal glances scores ($r (34) = 0.29; p = 0.09$) or between the post-training SMM scores and the internal glances scores ($r (34) = -0.081; p = 0.64$).

![Figure 33. Correlations between the Internal Glances Scores and the Mental Model Scores](image)

6.3.5. System Awareness

![Figure 34. Mean System Awareness Scores during each event type for across all three groups](image)
Analyses revealed that there was a main effect of Event Type ($\chi^2 (1, N = 36) = 11.473, p < 0.005$) on the participants’ mean System Awareness scores, where the mean scores were higher for the EE events (89.25) when compared to the NE events (71.67). However, there was no main effect of Training Group ($\chi^2 (2, N = 36) = 3.425, p = 0.18$) for the same. Overall, the VR group (88.89) had higher scores than both the BI group (79.27) and SD group (86.75), although this difference was not statistically different (Figure 34).

There was also no main effect of Training Group found when analyzing System Awareness scores considered only for the EE events ($\chi^2 (2, N = 36) = 3.086, p = 0.2136$). The VR group (93.442) had higher System Awareness scores than the BI group (83.87) and SD group (90.47), although not statistically significant. Similarly, there was no main effect of Training Group when considering the System Awareness scores only for NE events ($\chi^2 (2, N = 36) = 0.631, p = 0.7295$). Again, the VR group (75) had higher System Awareness scores than the BI group (65) and SD group (75), although not statistically significant.

A Pearson’s product-moment correlation test (Figure 35) was conducted to examine the correlation between the participants’ post-training mental scores (both GMM and SMM scores) and the System Awareness scores across all three groups. The correlation tests revealed no significant correlations between the post-training GMM scores and the System Awareness scores ($r (34) = 0.21; p = 0.23$) or between the post-training SMM scores and the System Awareness scores ($r (34) = 0.23; p = 0.17$).
6.3.6. Response Accuracy

Analyses revealed that there was a main effect of Event Type ($\chi^2 (1, N = 36) = 37.534, p < 0.001$) on the participants’ mean Response Accuracy scores, where the mean scores were higher for the NE events (76.39) when compared to the EE events (37.037). However, there was no main effect of Training Group ($\chi^2 (2, N = 36) = 0.374, p = 0.829$) for the same. Overall, the VR group (48.96) had higher scores than both the BI group (46.88) and SD group (44.79), although this difference was not statistically different (Figure 36).
There was also no main effect of Training Group found when analyzing Response Accuracy scores considered only for the EE events ($\chi^2 (2, N = 36) = 0.51, p = 0.774$). The BI group (40.28) had higher System Awareness scores than the VR group (36.11) and SD group (34.72), although not statistically significant. Similarly, there was no main effect of Training Group when considering the System Awareness scores only for NE events ($\chi^2 (2, N = 36) = 2.9231, p = 0.231$). The VR group (87.5) had higher System Awareness scores than the BI group (66.67) and SD group (75), although not statistically significant.

A Pearson’s product-moment correlation test (Figure 37) was conducted to examine the correlation between the participants’ post-training mental scores (both GMM and SMM scores) and the Response Accuracy scores across all three groups. The correlation tests revealed no significant correlations between the post-training GMM scores and the Response Accuracy scores ($r (34) = 0.21; p = 0.23$) or between the post-training SMM scores and the Response Accuracy scores ($r (34) = 0.23; p = 0.17$).

Figure 37. Correlations between the Response Accuracy Scores and the Mental Model Scores
CHAPTER 7.

DISCUSSION AND CONCLUSION

7.1. DISCUSSION

There is a major gap in literature regarding the relationship between training and mental models and hazard avoidance. This is made more complicated by the lack of literature in understanding hazard avoidance in the context of vehicle automation. The main goal of this dissertation research was to bridge these gaps by proposing a conceptual framework for hazard avoidance in the context of vehicle automation and understand how the behaviors associated with this new understanding of hazard avoidance could be measured and improved. Hazard avoidance for ADAS unlike traditional driving relies on the driver’s system awareness, i.e., awareness about one’s system status, as well as environmental awareness. Detection behaviors which used to include external cues and precursors for hazards now may also need to be extended to include glances at one’s instrument panel or other in-vehicle elements in order to understand the state of the system. Finally, vehicle control such as steering and braking may not be enough anymore, since additional system control related actions may also be important response when avoiding hazards while driving with ADAS and vehicle automation. Moreover, with a new understanding of hazard avoidance, new categories of hazards that now includes internal signifiers and precursors also become important when considering hazardous scenarios and when developing countermeasures such as training and educational materials. In an observational study, hazard avoidance behaviors from the proposed framework were verified and observed through the interactions and behavioral responses of experienced ADAS users. The observational study also yielded realistic outcome
measures to measure the various hazard avoidance behaviors. The insight gained from the observational study helped in conceptualizing, designing, and developing a training program. Using the immersive and realism properties of the VR headset, a highly interactive training program based on an error-based training approach was developed. This training program built up on past studies in training in both the driving and vehicle automation domain and provided the user with not only basic knowledge about ACC, but in-depth real-time tutorial on the various control mechanisms, display icons, system states, and limitations of ACC. Further, leveraging insights received from the observational study, a hazard avoidance component was featured in the training where the user would be trained about the appropriate responses and behaviors to adopt when encountering edge case situations. Finally, in a driving simulator study, the efficacy of the training method in improving driver’s mental models and hazard avoidance when using ACC was evaluated using a simulator drive featuring several edge case and normal events when driving with ACC. This brings us back to the proposed hypotheses generated from the first phase of research,

H1. Training impacts the drivers’ mental models about ADAS
H2. The training platform has an impact on the driver’s mental model
H3. Training affects driver’s mental model which in turn affects their System Awareness
H4. Training affects driver’s mental model which in turn affects their Lookout Behaviors
H5. Training affects driver’s mental model which in turn affects their System Control skills

In the upcoming subsections, we will discuss the results from the evaluation study and what the findings imply in terms of the hypotheses above.
7.1.1. Training impacts the drivers’ mental models about ADAS

The mental model scores were the General Knowledge scores or GMM scores which gauged the user’s general knowledge about ACC and its functionalities, and the Specific Knowledge scores or SMM scores, which gauged the user’s more nuanced knowledge about ACC system functions such as parameters and conditions required for change of ACC state or change within a particular ACC state. From the analyses it was revealed that training played an important role in the improvement of one’s general knowledge about ACC. All participants had a significant improvement in their GMM scores following their training. Both the Virtual Reality Headset-based training (VR) group and State Diagram visualization training (SD) group had higher GMM scores than their Basic Information (BI) group, although only the differences between the SD and BI groups were statistically significant. While analyzing the SMM scores, similar improvements in the participants’ specific knowledge about ACC was observed. However, no training group had any significant differences in their impact on the participants’ SMM scores. These results supports our hypotheses that training impacts driver’s mental models about ADAS.

It would be worth noting, however, that mental models are complex constructs that are hard to accurately characterize through outcome measures (Pradhan et al, 2020; 2021). Hence, it may be challenging to understand what the ceiling to one’s mental model is. In other words, it may be challenging to determine what constitutes a ‘perfect mental model’ about a particular concept. A ‘good mental model’ can be possessing knowledge about concepts with optimum level of detail in one’s mental model as required by the task to be performed (Keiras, 1988). It has been suggested that mental models depend on various factors such as user’s motivation, complexity of system, complexity of task, etc.
(Staggers & Norcio, 1993). We can reasonably assume that better mental models lead to more efficient usage of the system (Staggers & Norcio, 1993). In such cases, self-reported survey measures, although widely used for measuring mental models (Pradhan et al, 2022; Beggia & Krems, 2013; Gaspar et al, 2021), may not be able to holistically capture the calibration of one’s mental models and it may be prudent to involve other surrogate measures such as task-based error identification (Pradhan et al, 2020; 2021) to fully understand calibration of mental model levels.

7.1.2. The training platform has an impact on the driver’s mental model

From the earlier section, it was apparent that training platforms indeed differed in their effectiveness in improving the driver’s mental models. However, this effect was only limited to 24 GMM items which gauged their general knowledge about ACC and was not observed for the 50 SMM items. This could mean that in their current form, the training methods are efficient in improving the overall basic knowledge about ACC functions and limitations, however, training content may not be suitable to improve drivers’ more specific and nuanced knowledge about ACC. This once again highlights the importance of the role played by training content and framing of content (Singer & Jenness, 2020). Moreover, it would be worth noting that unlike past literature which may suggest driver’s do not read their informational content properly or only partially complete reading through their manuals (Mehlenbacher et al, 2002), in this study, the quiz component which captured the user’s knowledge and attention during the training process in real-time had an average score of above 80% accuracy which could mean that the participants took their training seriously and gained knowledge from their training method in real-time. Both the VR and SD groups had higher scores than the BI group which might mean that knowledge improves
more with the increasing level of detail and content provided in the training. However, the differences were not statistically significant.

7.1.3. Training affects driver’s mental model which in turn affects their System Awareness

The participants’ system awareness was measured through their verbal responses to audio-based probe placed at the end of each event in the simulator drive. The probe asked the participants questions about their system’s status during the drive thus monitoring their awareness of their system status. This measure was chosen following the review of possible outcome measures in Chapter 3 (Parasuraman et al, 2009). From the analysis, it was revealed that training did not have any significant effect on the participants’ system awareness. While the VR group had higher scores than their SD and BI counterparts, these differences were not statistically significant. Moreover, these results were also observed when analyzing separately for the system awareness scores of edge-case (EE) events and normal (NE) events, although overall the system awareness scores were significantly higher for EE events than the NE events. Furthermore, when performing correlation tests between the system awareness scores and the user’s corresponding post-training GMM and SMM scores, only weak non-significant positive correlations were found. These results reject our hypotheses that training affects driver’s mental models and in turn their system awareness when driving with ACC.
7.1.4. Training affects driver’s mental model which in turn affects their Lookout Behaviors

The driver’s lookout behaviors were characterized by both their external and internal glance scores. The external glance score was derived from the mean of two binary coded-glance responses towards the assigned target zone in each scenario. External detection glance was where the driver placed their gaze on the assigned target zone of the scenario within the launch zone. External assessment glance was characterized by the driver’s glance towards the target zone while passing it. Similarly, the internal glance scores were derived from the mean of the participants’ internal detection glance and the participants’ internal glance. The former required the participants to place their gaze on the instrument panel following their external detection glance, and the latter required the participants to place their gaze on the instrument panel after passing the target zone. From the analyses, it was found that training had no significant impact on the participants’ external glance scores. Similar to the earlier system awareness score, the VR group had higher scores than their counterparts in the BI and SD group, although these differences were not statistically significant. There was main effect of event type which meant that external glance scores were somewhat higher for NE events than for the EE events. On further analysis, it was found that training did not affect the external glance scores at all even when considering the EE and NE events separately. Correlation tests performed for examining any relationships between the mental model scores and external glance scores also revealed no significant correlations.

While there was no significant effect of training on the overall internal glance scores, the VR group had somewhat higher scores than the BI and SD groups. Further, there
were significant differences between the participants’ internal glance scores made during NE and EE events, where the scores were significantly higher for the EE group. This led to further analyses of the internal glance scores, where the scores for the EE events only were analyzed for any impact from training group. It was found that when considering the internal glances score for only the Edge Case events in the drive, the VR training had significantly higher scores than the BI group. It also had higher scores than the SD group, although the difference was not significant. No such effects of training were found when analyzing for the NE events separately. Correlation tests also yielded no significant correlations between the mental model scores and the internal glance scores.

These results may not be sufficient enough to support our hypothesis that training affects drivers’ mental models and in turn their lookout behaviors. However, the impact of the VR training which contained curated content about ACC edge case events and recommended areas of interest to gaze at when facing such events is quite evident from the results. It is also important to note that the areas of interest for glances or the target zones featured in all of the events were salient and this could have ensured perfect scores for external detection glances. Due to this, the external glance score may have had less variance across groups when compared to the internal glance score.

7.1.5. Training affects driver’s mental model which in turn affects their System Control skills

The participants’ response accuracy score represented their system control abilities. The response accuracy score was based on whether or not the driver’s carried out the recommended set of actions to avoid the hazards during the events. This measure was chosen following the review of possible outcome measures in Chapter 3 (Schleicher &
Analyses revealed that training did not impact the driver’s response accuracy score, and the scores for all groups were generally poor (below 50 on a 100 scale). The scores were significantly higher for NE events compared to EE events, particularly because NE events were events where ACC functioned as intended whereas EE featured events leading to ACC not functioning optimally and by nature were more complex. Correlation tests revealed weak non-significant positive correlations between the response accuracy scores and the mental models scores. These results essentially reject our hypothesis that training affects driver’s mental models and system control abilities. Moreover, when analyzing the count of the participants interactions with ACC which led to state changes, there were no significant differences between the interaction activities between the groups. This meant that when considering those interactions that either led to ACC active states or ACC inactive states, all participants had somewhat similar interactions with ACC. However, the participants had a much higher number of engaged and disengaged interactions for EE events than the NE events, which again could be due to the complexity of the EE events when compared to the NE events. Also, the participants appear to have applied more effort when responding to the EE events than for NE events, as indicated by their ACC interactions, but responded less accurately for the EE events than the NE events as indicated by their response accuracy scores. A previous study compared driver’s workload during complex and routine events and found that drivers who drove through both complex and routine events had experienced higher mental demand and perceived to have applied more effort during their drive than those who drove only routine events (Pai et al, 2023). Similarly, it has also been suggested that one’s workload may increase following an increase in their knowledge (Khastgir et al, 2019). Due to the scope of this
study, it is unknown whether there were any increases in driver workload following the training and if workload played a role in the participants’ ability to respond appropriately to the more complex edge-case events compared to simpler normal events.

7.2. LIMITATIONS, FUTURE WORK, AND IMPLICATIONS OF THE STUDY

7.2.1. Limitations and Future Work

The study has a few limitations as noted here. First, the evaluation study was conducted on a fixed-base driving simulator and an on-road study may help generalize these findings better. While this may be true, it may not be suitable to test the hazard avoidance behaviors of novice ACC users in an on-road setting where they would be vulnerable to real threats and hazards. Further, the edge-case events for ACC may not be easily encountered in the real-world and the simulator offers better experimental control and ability to design for various edge-case events. Second, the study only considered novice users of ACC, since it was evaluating the efficacy of training methods developed to improve the mental models and hazard avoidance of novice users. It may be interesting to contrast the effects of training on the mental models of experienced users and evaluate if their hazard avoidance skills are affected. Third, a large sample size may help in generalizing the results better. Fourth, the edge case events featured in the simulator drive featured salient hazards only. Future work could include latent hazards or latent target zones within the drive that may ensure more variability in the external glance behavior of the drivers. Future work could also identify categories of precursors for the new types of hazards in the vehicle automation context which would further benefit development of training and other countermeasures. Lastly, the mental model survey considered in this study was a self-reported survey and it is known that such self-reported measures suffer
from reliability issues and user bias (Schacter, 1999). Perhaps, it would be sensible to consider other surrogate measures such as task-based error identification (Pradhan et al, 2020; 2021) to holistically measure the calibration of one’s mental models.

Future work can also consider the effects of other driver characteristics such as age, background, sex/gender, technology acceptance, etc. on training and learning, and the outcome of training. While the study was not powered to consider these driver characteristics, literature shows that training could affect male and female drivers differently (Rosenbloom et al, 2007), as well as for older and younger drivers (Rosenbloom et al, 2007). Eye-tracking metrics such as ‘gaze dispersion’, ‘time taken to make first fixation’, ‘percentage of time spent at AoI’, etc. (Navarro et al, 2019; Stephenson et al, 2020) were not considered in this study. Future studies could utilize these measures to further investigate participants’ glance behaviors. The effect of workload due to training and exposure to complex events was not investigated in this study, and could be the scope for a future study.

The audio voice-overs in the VR training program were narrated by a synthesized male Caucasian voice. While the effects of voice types was not in the scope of this study, it would be worth noting that studies have shown increased engagement and preference towards real human voices than to synthesized voice (Craig & Schroeder, 2019). It has also been shown that real human voices facilitate better learning and credibility (Craig & Schroeder, 2017). The dialect of the voice could also have a better impact on the learning abilities if the dialect reflects the one’s own dialect (Finkelstein et al, 2013; Finkelstein, 2015). Future work could examine the effects of diverse voice-overs narrated by either human or synthesized voices in the VR training program.
A potential future work could also involve a debriefing session following the training to understand the user’s perceptions regarding different aspects of the VR training method. In the past, debriefing surveys have been used to understand the user’s own perceptions about improvement in knowledge, trust in the system, frequency of usage, duration of training, suitability of content of training, etc. (Pai et al, 2021). Such insights may be useful to update and improve upon the current training methodologies before extending them for other ADAS and vehicle automation features. It would also be interesting to consider different modes of learning using the VR platform. The VR training program developed for this dissertation research involved both text-based and audio-based instructions to accommodate both visual and auditory learners. However, an updated version of the VR training program could also include other modalities such as haptic feedback, since research has shown that multimodal learning is more effective than unimodal learning (Sigrist et al, 2013). Moreover, past studies have argued that audiovisual learning can improve driving performance and perception behaviors (Liu, 2001; Sigrist et al, 2013), while visuohaptic learning can be effective for spatiotemporal metrics such as reaction times and also to decrease mental effort (Van Erp & Van Veen, 2004; Sigrist et al, 2013). Eye-tracking metrics derived from the integrated eye-trackers available in certain VR headsets may assist in improving the training program. The VR headset used in this research had integrated eye-tracking, and a secondary analysis could be conducted using the eye movements of the users. This would give additional insights about the users’ perception of the training content in real-time and identify attention-grabbing or distractive elements that may have hindered learning. The eye movements will also help in understanding the user’s comprehension of the training content by...
recognizing instances where the video/audio instructions were not properly understood or followed by the users.

7.2.2. Implications of the findings

While the hypotheses were largely rejected except for the effect on mental models and internal glance scores as a result of the training methods, the findings are indeed promising. In most cases, although not statistically significant, the VR group outperformed their BI and SD group counterparts. This means that with more iterative testing and evaluations, the VR training program could prove to be an essential tool in improving driver’s knowledge about ADAS as well as their hazard avoidance when driving with ADAS. This is important, as VR becomes more and more accessible and cost effective as a developmental tool, it may be of interest to build on this research to develop and design training programs for other ADAS features or may be even for higher levels of automation.

The bigger picture one could take from this dissertation research is that research on hazard avoidance in the context of vehicle automation now has a tangible starting point with a conceptual framework which is useful in understanding the inherent differences between hazard avoidance in the automation context to that in the traditional driving context. Moreover, past literature has helped in updated the framework to include outcome measures for each behavioral construct of hazard avoidance and future research works can investigate aspects of hazard avoidance that were not investigated in this study, such as glance scan pattern and gaze dispersion and reaction times. The observational study was also instrumental in capturing the initial findings of how experienced drivers interact with ACC and respond to hazards when driving with ACC. The next step would be to replicate an observational study to include novice ACC users, so the inherent differences between
novice and experienced ACC users can be mapped. This in turn, may help fill in the gaps and improve our understanding of hazard avoidance better, leading to better and more effective training paradigms. Better training practices may shape future policies and laws regarding vehicle automation features and influence the vehicle and system design of newer vehicles in a rapidly developing automobile industry.

BIBLIOGRAPHY


Madigan, R., & Romano, R. (2020). Does the use of a head mounted display increase the success of risk awareness and perception training (RAPT) for drivers? Applied Ergonomics, 85(February), 103076.


Pradhan, A. K., Pollatsek, A., Knodler, M., & Fisher, D. L. (2009). Can younger drivers be trained to scan for information that will reduce their risk in roadway traffic scenarios that are hard to identify as hazardous?. *Ergonomics*, 52(6), 657-673.


attention training on the duration of novice drivers’ glances inside the vehicle. 
Ergonomics, 54(10), 917–931.


SAE. (2018). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. SAE International: Warrendale, PA, USA.


