Behavioral Adaptation to Driving Automation Systems: Guidance for Consumer Education

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ABSTRACT

Researchers have postulated that the implementation of driving automation systems could reduce the prevalence of driver errors, or at least mitigate the severity of their consequences. While driving automation systems are becoming increasingly common on new vehicles, drivers seem to know very little about them. The following dissertation describes an investigation of driver behavior and behavioral adaptation while using driving automation systems in order to improve consumer education and training. This dissertation uses data collected from test track environments and two naturalistic driving studies, the Virginia Connected Corridor 50 (VCC50) Vehicle Naturalistic Driving Study and the NHTSA Level 2 Naturalistic Driving Study (L2 NDS), to investigate driver behavior with driving automation systems and make suggestions for modifications to current consumer education practices. Results from the test track study indicated that while training strategy elicited limited differences in knowledge and no difference in driver behaviors or attitudes, operator behaviors and attitudes were heavily influenced by time and experience with the driving automation. The naturalistic assessment of VCC50 data showed that drivers tended to activate systems more frequently in appropriate roadway environments. However, drivers spent more time looking away from the road while driving automation systems were active and drivers were more likely be observed browsing on their cell phones while using driving automation systems. The analysis of L2 NDS showed that drivers' time gap preferences changes as drivers gain experience using the driving automation systems.

Additionally, driver eye glance behavior was significantly different with automation use and indicated the potential for an adaptive trend with increased exposure to the system for both glances away from the roadway and glances to the instrument panel. The penultimate chapter of this work presents training guidelines and recommendations for consumer education with driving automation systems based on this and other research that has been conducted on driver interaction with driving automation systems. The results of this research indicate that driver training should be a key focus in future efforts to ensure the continued safe use of driving automation systems as they continue to emerge in the vehicle fleet.

An Assessment of Operator Behavioral Adaptation to Driving Automation Systems and Training Guidelines

Alexandria Marie Noble

GENERAL AUDIENCE ABSTRACT

While driving automation systems are becoming increasingly common on new vehicles, drivers seem to know very little about them. Previous studies have found that owners of vehicles equipped with advanced technologies have demonstrated misperceptions or lack of awareness about system limitations, which may impact driver comfort with and reliance on these systems. Partial driving automation systems are designed to assist drivers in some vehicle operation demands, they are not, however, designed to completely remove the driver from the driving task. The following dissertation describes an investigation of driver behavioral adaptation while using driving automation systems with the goal of improving consumer education and training.

DEDICATION

To my family.

"Where the women are strong."

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Chapter 1. Introduction

In 2016 there were 34,439 traffic fatalities in the United States, 94% (±2.2%) of these fatal crashes were a result of the choices made by drivers (National Center for Statistics and Analysis, 2018; National Highway Traffic Safety Adminitstration, 2018). Recognition errors which include inattention, internal and external distractions, and surveillance errors (41% ±2.2%) was the most frequently assigned critical reason for crash involvement (National Center for Statistics and Analysis, 2018). Decision errors were the second most frequent and included driving too fast for conditions, false assumption of other's actions, illegal maneuver and misjudgment of gap or others' speed. This category accounted for approximately 33 percent (±3.7%) of all crashes (National Highway Traffic Safety Adminitstration, 2018). It is evident that drivers are the single largest factor influencing transportation safety in the United States. In order to reduce the unacceptable volume of traffic fatalities countermeasures should focus on reducing human errors.

Researchers have developed a wide range of countermeasures to address human errors including improved perception of roadway through lane markings, roadway signing, and rumble strips (Finley, Funkhouser, & Brewer, 2009; Gibson & Crooks, 1938). These traditional countermeasures have been complemented by more technologically sophisticated methods as the costs of hardware (e.g., cameras and sensors) decline and computing systems demonstrate higher processing capabilities. Specifically, researchers have postulated that the implementation of driving automation systems could reduce the prevalence of driver errors, or at least mitigate the severity of their consequences (Blanco et al., 2016; Scanlon, Kusano, Sherony, & Gabler, 2015b, 2015a; Stanton & Salmon, 2009). Research indicating that over 30% of traffic fatalities could be prevented through the use of these systems emphasizes the significant benefits that could be achieved through the deployment of driving automation systems (Jermakian, 2011; Reagan,

Cicchino, Kerfoot, & Weast, 2018).

In fact, the prevalence of driving automation systems as a standard feature or part of an optional package increased between the 2016/2017 and 2018/2019 model years (Consumer Reports, 2019a). One contributing factor to this increase may be the support demonstrated by the federal government toward the goal of broad deployment through the development of voluntary guidance. This guidance is intended to support the automotive industry and other key stakeholders as they consider best practices relative to the testing and deployment of automated vehicle technologies (U.S. Department of Transportation, 2016, 2017). The demand of these systems is also driven in part by consumer desire to possess new-vehicle technologies (Ankem, Noble, Miles, & Klauer, 2019) and original equipment manufacturers' (OEM) desire to improve safety for their customers.

Regardless of the underlying reasons for their continued popularity, it is clear that automated driving systems promise to impact transportation safety in beneficial ways. However, it is important to note that the purported benefits of automated driving systems may not fully materialize unless drivers use them appropriately. A myriad of inquiries on driver knowledge and use of automated driving systems have shown that these systems are misunderstood by operators with regard to their capabilities and limitations and often times misused (Larsson, 2012; McDonald, Carney, & McGehee, 2018a; McDonald et al., 2015, 2016; McDonald, Reyes, Roe, & McGehee, 2017; C. M. Rudin-Brown & Parker, 2004).

It is this notion of how drivers may use or misuse driving automation systems that is the central focus of this dissertation. Specifically, how do drivers adapt to driving automation systems over time, are these adaptations supportive of improved transportation safety, and what are some of the factors that influence adaptation? To achieve the maximum safety benefits of driving

automation systems these questions must be addressed. The remainder of this introduction will provide an overview of the prior literature which serves as the foundation for the development and conduct of this work.

A summary of the SAE International Levels of Driving Automation will be provided to offer context for the importance of user knowledge of system capabilities and limitations as well as the roles and responsibilities associated with each level of automation. This will be followed by an overview of the driving task and a description of how the introduction of automation alters the role of the vehicle operator. The theory of driver adaptation through the lens of perceived and desired risk as well as the possible adverse outcomes of behavioral adaptation as it pertains to the use of driving automation systems including disuse and misuse will then be discussed. The penultimate section will discuss factors that influence behavioral adaptation in the human-machine relationship, because these elements can influence the degree to which benefits of driving automation systems can be derived. The final section will discuss one possible mechanism for staving off negative adaptive driver behaviors, improving driver training practices for driving automation systems. The introduction will conclude with a summary of key research gaps and the objectives and questions that serve as the foundation of this dissertation.

Driving Automation Systems – SAE Levels of Driving Automation

Differentiating the levels of driving automation from one another can be a daunting task. The Society of Automotive Engineers developed a taxonomy (SAE J3016) to define and standardize the levels of driving automation. The SAE Levels of Automation range from level 0, no driving automation to level 5; full driving automation. Figure 1 shows the description of the each level of automation as defined by SAE J3016, which attempts to clarify the human role, if any, during driving automation engagement (SAE International, 2018). The lower levels of driving

automation, which are available today on vehicles, consist of levels 0 – 2. Whilst using levels 0 – 2, the human operator is responsible for the constant supervision of the support features and is responsible for maintaining safety.

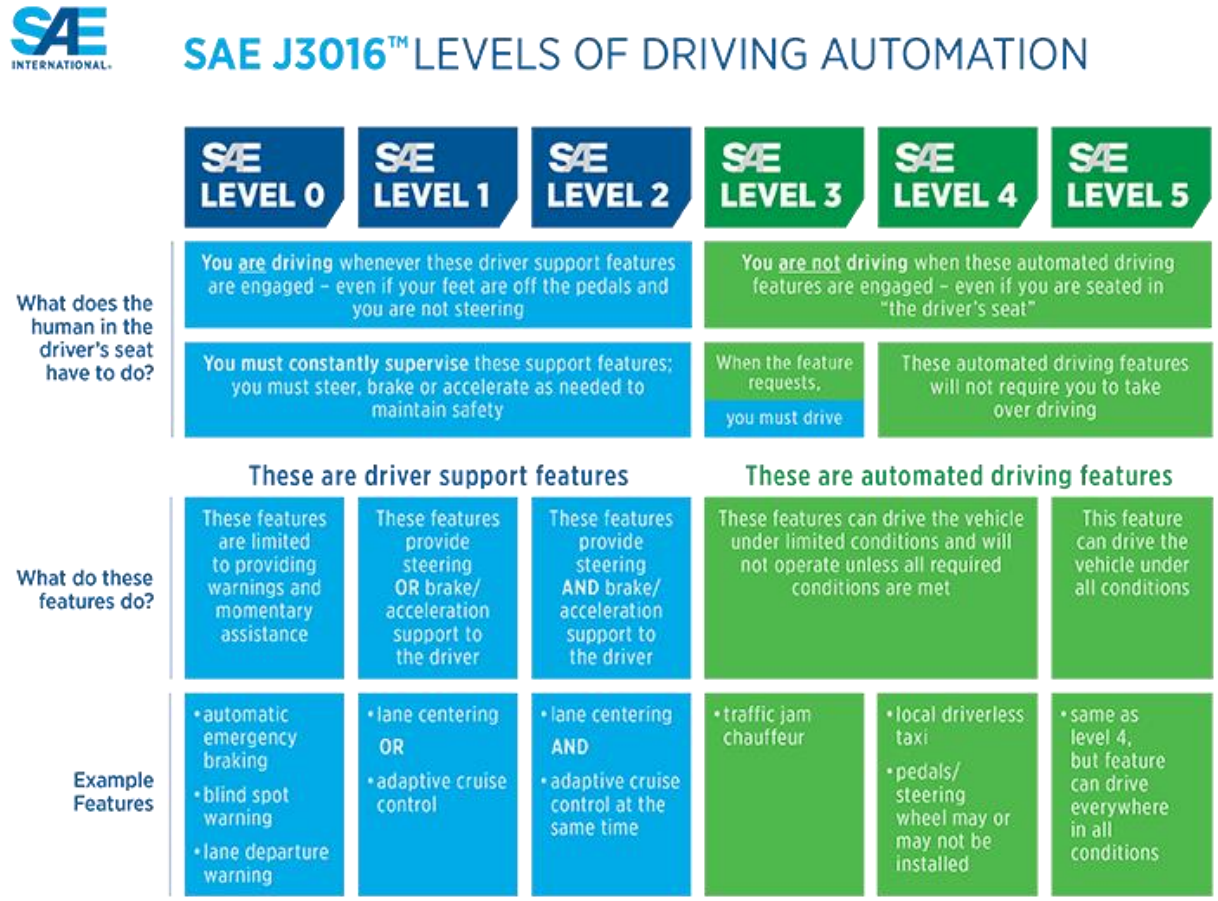

Figure 1. SAE Levels of Driving Automation (SAE International, 2018)
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The primary level of automation discussed in this dissertation will be limited to level 2 – Partial Driving Automation (L2). The example support features shown in Figure 1 for level 2 include the simultaneous use of adaptive cruise control and lane centering systems, which are often referred to as lane keeping systems. A detailed description of these systems follows.

Adaptive Cruise Control Adaptive cruise control (ACC) simplifies the task of driving because it relieves the driver of the mentally demanding task of monitoring the vehicle's speed and proximity to other vehicles (Reif, 2014). According to SAE J2399, Adaptive Cruise Control (ACC) is an

enhancement of conventional cruise control which allows the ACC-equipped vehicle to follow a forward vehicle at a pre-selected time gap (e.g., clearance, following distance) up to a driver selected speed (SAE International, 2014). The control of vehicle spacing is achieved through automated control of the engine, powertrain, and/or service brakes. The main area of application for ACC is on expressways and multi-lane roads with light to relatively heavy traffic densities (Reif, 2014). Typical ACC system components include a ranging sensor (e.g., millimeter wave radar), optical sensor, engine management with electronic torque control, and electronic braking modulation (Reif, 2014; Tsugawa, 2006).

Lateral Control Systems

The primary function of lateral control systems is to assist drivers with maintaining their current travel lane. These systems generally use forward facing cameras and machine vision to detect lane markings on the road and one or more vehicle control functions (steering, braking, drive torque) to ensure the vehicle remains within its lane (SAE International, 2016a; Tsugawa, 2006).

Lateral control systems can offer different degrees of assistance depending on what type of system a vehicle is equipped with, two types of lateral control systems are available: lane keeping and lane centering systems. Lane keeping assistance (LKA) can detect lane markings and will notify the driver if any unintentional lane deviations are detected. If the driver does not respond in time, LKA will provide corrective steering to keep the vehicle within the current lane. The more advanced iteration of lateral control is called Lane Centering Assist (LCA), which attempts to keep the vehicle centered within its current lane of travel, within the system's operational design limitations. Both systems are often referred to collectively as LKA despite the functional dissimilarities which contributes to consumer confusion and expectations for system

performance. According to Consumer Reports (2019b), many consumers do not understand the difference between systems that activate to keep the vehicle from departing the lane and systems which continually keep the vehicle centered in the lane.

The Driving Task and Driving with Automation

Although we often think of driving as a relatively simple task involving starting a car and controlling acceleration, deceleration, and steering to get from point A to B, this is an over simplification. Operating a vehicle is a complex task that involves, for example, constantly tracking and predicting the path of objects (e.g., cars, trucks, pedestrians), continuously controlling a vehicle's position and speed, and determining a proper route. The complexity increases substantially under unique conditions such as nighttime or inclement weather. The availability of driving automation systems adds an additional layer of complexity. Driver behavior models allow researchers to represent the aggregate behavior of the driving population or the information processing of an individual driver. This is important for understanding how the current state and changes to the complexity of the driving environment and vehicle may impact driver performance.

One construct in particular, by John Michon (1985) is the foundation of SAE J3016. Michon's model uses a hierarchical approach and is essential to understanding the driving task for both assisted and unassisted driving situations. A second construct is Gibson & Crook's "field of safe travel", which examines human performance from an ecological perspective using a conventional automobile. Gibson & Crook's "field of safe travel" is essential to understanding the requirements for the safe use of driving automation as it considers other road users and the driving environment.

Michon's Driver Behavior Model Michon (1985) developed three levels of skills and control for the driving task specifically. The three levels are: strategic (planning), tactical (maneuvering), and

operational (control). These levels were defined according to the time and attention required for the sub-task at that particular level (Louw, 2017; Reason, 1987).

The *control level* sub-tasks are the simplest tasks and involve controlling the vehicle's lateral and longitudinal position on the road through braking and steering. These sub-tasks are completed through automatic action over a very short period of time (milliseconds). The *tactical level* describes how drivers maneuver the vehicle through control inputs, allowing them to negotiate through the driving environment based on the prevailing circumstances. Driving maneuvers are largely constrained by the affordances of the environment (Gibson, 1979; Gibson & Crooks, 1938). This stage involves tactical decisions and maneuvers by drivers to particular situations to achieve pre-determined goals. Sub-tasks at the tactical level occur in a matter of seconds. The *strategic/planning level* is the most advanced stage, this stage requires developing the goals of the driving task such as navigating to the destination, as well as specifying the sub-goals such as route selection. The planning stage of driving takes more time to plan and execute than other stages of the driving task.

Gibson & Crooks – Field of Safe Travel

In conventional driving, the driving task is primarily a perceptual task with vehicular control tasks being simple and easily learned. For both conventional driving and assisted driving however, it is essential that the operator of the vehicle obtains information from the forward visual scene (Gibson & Crooks, 1938). Gibson and Crooks described the *field of safe travel* as the roadway environment consisting of safe and unsafe areas. Typically the safe location was considered the middle of the roadway while an unsafe location was generally identified as general obstructions or physical road boundaries (e.g., curbs, ditches, or other vehicles). During the process of locomotion obstacles are met with and the field of safe travel may shift so that locomotion may

be appropriately modified to avoid them. This process is guided by direct perception.

When drivers are not actively monitoring the roadway regardless of whether they are assisted by driving automation or not, the boundaries of the field of safe travel may shift without their knowledge. Furthermore, misperceptions about driving automation system capabilities and performance limitations may influence the driver's perception of the field of safe travel. Therefore, it is imperative that drivers' have adequate knowledge of their driving automation systems and pay sufficient attention to the road whilst using driving automation systems.

Driving with Automation

When level 2 driving automation systems are active on equipped vehicles, it is important to note that only part of the dynamic driving task (DDT) is performed by the driving automation system. The DDT consists of all of the real-time *operational* and *tactical* functions required to operate a vehicle in on-road traffic, explicitly excluding all strategic functions (Table 1). While driving automation systems are active, the driver is responsible for supervising the feature's performance. Driving automation systems are intended to support the driver in performing the DDT within the Operational Design Domain (ODD) specified for the systems. The driving automation systems do not replace, a driver in performing the DDT and are not intended to operate outside of their specified ODD. In order for the DDT to be completed successfully, all components must be completed by a human driver, a driving automation system, or a combination of the two (SAE International, 2018).

Table 1. SAE Dynamic Driving Task Component for Level 2 Driving Automation with Michon's task levels

SAE DDT Component	Michon's Levels	Completed by Driving Automation
Lateral vehicle motion control via steering	Operational	X
Longitudinal vehicle motion control via acceleration and deceleration	Operational	X
Monitoring the driving environment via object and event detection, recognition, classification, and response preparation	Operational & tactical	
Maneuver planning	Tactical	
Enhancing conspicuity via lighting, signaling and gesturing, etc.	Tactical	

The second and possibly most difficult component of the DDT is the *Object and Event Detection and Response (OEDR)* subtask. This subtask involves monitoring the driving environment as well as executing the appropriate response to events. This can include driving events associated with system actions such as undiagnosed driving automation system errors or state changes. A level 2 driving automation feature is capable of performing limited OEDR (SAE International, 2018). However, there are some events that the driving automation system is not capable of responding to which ultimately require human operator intervention. This is why it is the responsibility of the driver to supervise the driving automation system performance by completing the OEDR subtask of the DDT. However, if the human operator is not alert and therefore, unaware of changes in the environment they may not have sufficient time or ability to respond to obstacles.

The introduction of driving automation to the driving task changes the driver's role from an active participant to a passive supervisor. These alterations could result in behavioral changes in the driver, especially if this increase in technological assistance is coupled with lack of

knowledge of driving system performance. One concern is that as more rapid control subtasks (e.g., lane and speed maintenance) are being handled by the driving automation, the human operator may neglect to effectively perform the OEDR subtask. This concern is not unfounded as research on human-automation interaction in other domains has indicated that operator behavioral change may result from lack of relevant experience with the given task demands (Stanton & Young, 2005), vigilance decrements associated with reduced workload (Endsley & Kiris, 1995; Louw et al., 2017; Louw & Merat, 2017; Merat et al., 2019; Strand, Nilsson, Karlsson, & Nilsson, 2014) or complacency with the automated systems (Bahner, Huer, & Manzey, 2008; Manzey, Bahner, & Hueper, 2006; Singh, Molloy, & Parasuraman, 1993b, 1993a).

Driver Behavior and Behavioral Adaptation

System designers often assume that technology will be used in planned and predictable ways, in alignment with the systems intended use cases; however, this assumption is not warranted given humans' demonstrated capability to generate workarounds to common situations (Alter, 2014; Debono et al., 2013; Seaman & Erlen, 2015). It is not unreasonable to expect drivers to alter their behavior when driving automation systems are active beyond the scope of what would be anticipated by a system designer. For example, the designer's intention may be that the human relinquishes lateral and longitudinal control of the vehicle to the driving automation system while the human driver continues performing the OEDR subtask in earnest. However, with time, experience, and familiarity with driving automation systems, the human operator may stop performing the OEDR subtask in favor of a more leisurely task (e.g., texting, napping, or reading).

The most often used definition for behavioral adaptation comes from the Organisation for Economic Cooperation and Development (OECD). This committee of experts were tasked with the responsibility to review to what extent and in what direction drivers adjust their behavior in

response to system changes which are designed to improve safety. The OECD (1990) defines behavioral adaptation as the collection of *"behaviors which may occur following the introduction of changes to the road–vehicle–user system and which were not intended by the initiators of the change"* (p. 23). This definition is highly generalizable and encompasses all aspects of behavioral adaptation as it pertains to driving automation systems. Maximizing success and minimizing the likelihood of unintended negative consequences can be achieved by anticipating potential behavioral changes or by more accurately predicting when and under what circumstances behavioral adaptation is likely to occur (Rudin-Brown & Jamson, 2012). How drivers use their driving automation systems may be influenced by their inclination to alter their behavior based on their perception of the system's capability under specific conditions.

Behavioral Adaptation and Risk

Early studies of behavioral adaptation were spurred by Taylor's (1964) study examining galvanic skin response (GSR) during driving which led to the development of zero-risk theory (Näätänen & Summala, 1974; Summala, 1988), risk compensation (O'Neill, 1977; Peltzman, 1975), and risk homeostasis (Trimpop, 1996; Wilde, 1982). Risk compensation and risk homeostasis function under the principles of a perception–evaluation process, with behavior adjustment regulated by feedback. This behavior adjustment is assumed to be influenced by individual capabilities and situational factors. The basic ideas behind these theories are 1) people have an awareness of a level of risk that they are willing to endure, 2) they have a level of risk that they are willing to accept (often referred to as their *target level of risk*), and 3) they are generally able to perceive their current level of risk. However, many behavioral adaptation theories fail to consider experience and time explicitly. This omission was recognized by Fuller (2000) which led to the development of Risk Allostasis Theory (RAT).

Risk Allostatis. Allostasis is defined as the process by which a state of internal, physiological equilibrium is maintained by an organism in response to actual or perceived environmental and psychological stressors (Merriam-Webster, 2019). RAT refers to adaptation to a dynamic target condition and is defined as maintaining certain conditions that vary according to an individual's needs and circumstances (Fuller, 2011). This theory considers the definition of target risk for different drivers and situations, not through statistical analysis, but through an inferred cost-benefit analysis of safe and risky behavioral choices. This cost-benefit analysis supersedes the other factors such as perceived capability, journey goals, effort motivation, disposition identified in RAT (Fuller, 2011).

Fuller notes that the effects of risk feelings on decision making are not binary, rather they are continuously present and constantly evaluated. This constant evaluation of task difficulty and perception of risk informs driver decision making, either consciously or sub-consciously. However, only when the threshold point of subjective risk is reached do risk feelings become salient to the driver (Fuller, 2011, p. 31). One of the key predictions of RAT is if drivers experience a change in workload which reduces task demand below the driver's acceptable range, then the driver will seek to increase task demand in some other way, possibly by undertaking other tasks such as searching the radio or using their mobile phone (Kinnear & Helman, 2013). This concept applied to driving automation systems is concerning as these systems are designed to reduce workload and users are generally ill-informed about system capabilities and consequently, may perceive the workload reduction to be greater than it actually is. Therefore, drivers may believe they are able to undertake other tasks in lieu of completing the OEDR subtask.

Possible Adverse Outcomes of Behavioral Adaptation with Automation

The premise of reinforcement is that under particular stimulus conditions, behavior that is

followed by rewarding consequences becomes strengthened relative to other behaviors which could occur under those same conditions (Fuller, 2007). The concept of reinforcement has been used in psychology to explain changes in behavior that reflect learning. Prior work has been conducted using animals as subjects with reinforcers or punishers such as food or electric shocks. However, in the driving domain, research on the concept of reinforcement is rather sparse with some notable exceptions, such as intelligent speed advisory systems and seatbelt use (Reagan, Bliss, Van Houten, & Hilton, 2013; Reinhardt-Rutland, 2001). Reinforcement is the primary mechanism behind Operant Conditioning (Skinner, 1953), the basic operant model of conditioning is the three-term contingency:

$$A\ (Antecedent) \rightarrow B\ (Behavior) \rightarrow C\ (Consequence)$$

The antecedent is the stimulus event that precedes the target behavior. The behavior is the action that the individual exhibits in response to the stimulus, and the consequence is the behavior or stimulus that immediately follows the behavior. One type of consequence is a reinforcer, which increases the probability that the response will be emitted in the future. One example of a positive reinforcer is performing a secondary task while utilizing vehicle automation; the behavior of secondary task engagement is strengthened by the presence of driving automation system activation when the automation is working properly. The other type of consequences are known as punishers. Punishers are a consequence that decrease the likelihood of a behavior occurring (Schunk, 2012). In situations where drivers experience a punishment such as a crash, near crash, or violation of expectations associated with the use of L2 systems, they may suspend a secondary task activity or disuse automated systems for a period of time.

If a behavior, its antecedents, and its consequences are observable and measurable then behavior can be predicted (Skinner, 1953). This means that if we can measure behavior of the driver while utilizing driver assistance systems, along with the antecedents and associated

consequences, then we can predict how drivers will react in different situations (e.g., situations where drivers will be more likely to engage in secondary tasks). Any unintended behavior that emerges and is sustained does so for a reason: the behavior is reinforced and the driver learns which circumstances afford the opportunities that provide benefits (Fuller, 2007; Vaa, 2013). Thus, drivers' responses in the presence of driving automation systems can be observed in both controlled settings and by observing how drivers interact with driving automation on public roadways. These observations of driver behavioral change with increased exposure is a form of learning, as drivers learn to trust the systems they may behave differently over time.

Automation Disuse

Operators may dislike or mistrust the driving automation systems and may suspend use or stop using the system completely. System disuse would eliminate any possible benefit of the automated system. Distrust describes a system in which the user believes that the automation's performance is less than it actually is. A survey study conducted by Eichelberger and McCartt (2016) found that approximately a quarter of drivers received lane departure warnings they perceived were unnecessary. Only 13% of drivers surveyed in this study used the lane keeping assistance system (in these models the system was off by default). However, Eichelberger and McCartt note that in other studies where the default of the LKA system is "on" there is still a high disuse rate (31 – 49%).

Automation Misuse

Automation misuse results from over trust in the system or complacency. Billings (1976) defined complacency as self-satisfaction which may result in non-vigilance based on the unjustified assumption of satisfactory system state. Complacency has been mentioned as a potential negative effect of automation (Metzger & Parasuraman, 2001; Parasuraman, Molloy, &

Singh, 1993; Singh et al., 1993b). Therefore, counter-measures such as driver monitoring systems are being deployed to supervise the driver during periods of automation system activation to prevent this type of behavior (SAE International, 2018). Complacency leads to a failure to monitor an automated system, hence, failure to notice when a fault occurs. With an increase in the reliability of automation comes a decrease in failure events. To this end, automation failures may be missed altogether because they become a rare occurrence and user faith in the automated systems is high (Molloy & Parasuraman, 1996; Sebok & Wickens, 2017; Wickens et al., 2009).

It was noted by Mosier & Skitka (1996) that operators can sometimes rely on automated cues as a heuristic replacement for attentive information seeking and processing. Onnasch et al. (2014) found that operators had difficulty troubleshooting system performance issues and recovering from unexpected system errors When operators stop monitoring the "raw data" during long periods when alerts are silent (or not activated) they can turn their attention elsewhere to support concurrent tasks. This is described as a high reliance on automation (Dixon & Wickens, 2006; Meyer, 2001).

Frequently, these issues have been attributed to the operator's tendency to reduce their monitoring of highly reliable automated systems (Parasuraman, Sheridan, & Wickens, 2008). This was observed by Mosier et al. (1998) where automation bias played a significant role in pilot interaction with automation aids and monitoring the environment. Llaneras et al. (2013) also showed that when a driver was given the opportunity to relinquish control of lateral and longitudinal operations over to a simple but reliable automated system, most drivers will engage in moderate to complex secondary task activities.

Misperceptions of system capabilities and limitations can encourage the misuse or disuse of driving automation systems. Training drivers is one way to reduce the likelihood of these

maladaptive behaviors occurring or to correct them at the onset of complacency. Research has shown that by training operators about a system's actual reliability it is possible to alter trust and reliance patterns (Koustanaï, Cavallo, Delhomme, & Mas, 2012; Masalonis & Parasuraman, 2003) and reduce complacency (Manzey et al., 2006).

Factors Influencing Behavioral Adaptation

A myriad of factors can influence a driver's propensity to behave a specific way from one moment to another. The psychosocial characteristics of the potential user may influence driver behavior while using driving automation systems (Rudin-Brown & Noy, 2002; Rudin-Brown & Parker, 2004; Stanton & Young, 2000). For example, drivers who are technology-averse may be less willing to utilize automated systems whereas those who are technologically-inclined may inadvertently place too much trust in their driving automation systems. Additional factors for consideration of driver behavioral adaptation to driving automation systems are described below.

Technology Acceptance

The Technology Acceptance Model (TAM) (Davis, 1989, 1993) considers the actual use of the technology as a mediating factor of user acceptance of a system, but neglects to consider how actual use affects future use. Ghazizadeh et al. (2012) extended the TAM to create the Automation Acceptance Model (AAM) shown in Figure 2. This modification includes the explicit additions of trust and compatibility as well as a feedback mechanism. The feedback mechanism stems from "Actual System Use" which will further inform the constructs of trust, perceived ease of use, compatibility, perceived usefulness, and the behavioral intention to use. This indicates that that the amount and nature of a user's interaction with the driving automation system will influence their trust in the system and potentially their behaviors while the system is being used.

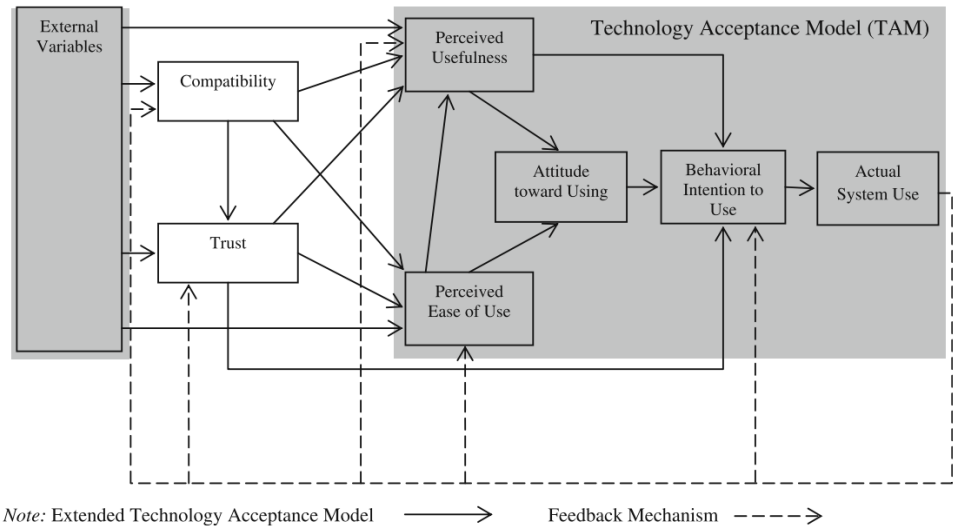

Figure 2. The Technology Acceptance Model as augmented by Ghazizadeh et al. (2012) to create the Automation Acceptance Model.
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Trust

The construct of trust is complicated and multi-facetted, however, the outcome of inappropriate trust/reliance on automation is simple. When operators do not exercise appropriate trust in vehicle automation the full benefit of these systems is unable to be attained. In their review of the varying definitions of trust, Lee & See (2004) identified a general theme of expectations regarding behaviors or outcomes. Hoff & Bashir (2015) suggested that trust was divided into three distinct categories; dispositional, situational, and learned. Each level of trust is influenced by unique factors that are specific to the user, the context, and the operator's experience with the system under evaluation.

Dispositional trust. Dispositional trust is independent of the context or system. Numerous psychometric scales exist to measure one's tendency to trust (Rempel, Holmes, & Zanna, 1985; Rotter, 1980). Merritt and Ilgen (2008) found that individuals with high levels of dispositional trust in automation were more likely to trust reliable systems; however, their trust in particular

may decline more considerably following system errors, likely due to having their expectations violated.

Situational trust. Situational trust depends on multiple factors including: the environment, the automated system, and the context-dependent characteristics of the human operator. The external factors related to the driving automation system include system type, complexity, perceived risk, and perceived benefits, while user related factors include self-confidence, expertise, mood, and attentional capacity. When users have sufficient cognitive resources available, they may be able to engage in the analytic process of trust formation by rationally evaluating the salient characteristics of the system. However, when cognitive resources are constrained, the users are more likely to rely on analogic and affective thought processes (Lee & See, 2004).

Learned trust & dynamic learned trust. Learned trust draws from the user's experience or current interaction with a given system. Learned trust in a driving automation system is directly influenced by pre-existing knowledge and bias along with the performance of system. In theory, learned trust is closely linked to situational trust because in many cases, automated systems must be used for trust to grow (Muir & Moray, 1996). Using automation provides users with the opportunity to observe how the system works and thus develop trust, whereas disusing automation stifles the growth of trust. However, there are a multitude of factors that can influence trust before any interaction with a driving automation system has occurred (e.g., a system's reputation, commercials, and other informational material; Hoff & Bashir, 2015). Learned trust is also dynamic in that it continues to change with increasing exposure to the automated system. It can also be influenced by system design features, which can alter the user's perceptions of system

performance (Louw, Kountouriotis, Carsten, & Merat, 2015; Parasuraman, Bahri, Deaton, Morrison, & Barnes, 1990; C. M. Rudin-Brown & Noy, 2002; Sarter & Woods, 1995).

The Qualitative Model of Behavioral Adaption hypothesizes that the degree of behavioral adaptation will be related to the amount of trust a user has in the system. Rudin-Brown and Noy (2002) found that drivers reported a higher degree of trust in both the reliable systems and those systems which provided false alerts after exposure. Interestingly, they also found that driver beliefs about the system's reliability persisted to future exposures, regardless of the system's performance during subsequent interactions. Given user's propensity to trust unreliable automation there is a strong motivation for setting clear expectations regarding system purpose, limitations, and driver responsibility. Assisting drivers in developing a sufficiently accurate mental model of system capabilities and their role in the human-machine relationship will help facilitate appropriate use of driving automation systems and assist in managing user expectations.

Mental models and perceived system capability

When given no other guidance, users will look to the visible components, observe system behavior, and then make guesses about "how the system works" creating their own mental model, which may be vastly different from the intended purpose of the designer. A user's mental model can differ, often significantly, from the designers intentions due to varying prior knowledge, individual abilities, and different beliefs about the purpose and function of the system (Jonassen, 1995). Having an accurate mental model will appropriately guide user behavior and predictions about system behavior. Having an inaccurate mental model will lead to user errors and inaccurate predictions about system activity. When drivers lack appropriate understanding of automated systems, the consequences can be misuse or underuse, which undercuts the potential benefits of these technologies. This can also lead to gaps in knowledge that consumers will fill on their own,

potentially with inaccurate information or beliefs derived from limited exposure or observation.

The mental models of driving automation systems and trust represent an emerging and important area of research. Beggiato & Krems (2013) evaluated mental models and trust in adaptive cruise control (ACC), a widely deployed advanced driver assistance system. Study participants were provided with one of three descriptions of the ACC system: (1) correct (all accurate information presented); (2) incomplete (only presented accurate information but omitted some of key accurate information); or (3) incorrect (included some accurate and some inaccurate information). The questionnaire-based assessment of participants' mental models then indicated that their mental models improved with experience using the ACC system.

Exposure and Experience

Exposure has serious implications for information seeking and the potential for the development of misperceptions of system capabilities. In 1983, Godfrey, Allender, Laughery, & Smith found that the more hazardous consumers perceive a product, the more likely consumers are to look for warning. Furthermore, Tversky & Kahneman (1971) argued that individuals tended to place undue confidence in observed behaviors during early exposures. Thus, this confidence can result in misunderstandings that are not corrected through the natural course of error free driving. These findings were corroborated in a report by McDonald et al. (2018a) where owners of vehicles with driver assistance systems have self-reported potentially dangerous behavioral adaptation such as high risk secondary task engagement while using adaptive cruise control. These maladaptive behaviors may pose significant challenges to those responsible for designing, conducting, and evaluating safety systems and operator training (Manser, Creaser, & Boyle, 2013).

In order to understand the nature and magnitude of risks associated with driver behaviors and to develop effective countermeasures, it is necessary to employ measures that adjust for

exposure (Szklo & Nieto, 2014). Manser et al. (2013) discussed the temporal factors that may affect driver behavior after the introduction of a change in the road system (such as the interaction with new in-vehicle equipment or behavioral shift after an event). Three points of driver exposure to the implemented change are mentioned: 1) the immediate phase, which occurs immediately after a driver experiences the change; 2) the short-term phase, occurring hours, days or weeks after the introduction of the change; and 3) the long-term phase, which transpires after months or years. These stages may be considered when examining behavioral adaption relative to safety system use as the quality of the performance is a result of the introduction of a system as well as considering how driver behaviors change as a function of their use of the system.

Driver Training for Driving Automation Systems

In level 2 driving automation systems, the automated systems perform the lateral and longitudinal control subtasks of the DDT that are redundant to the driver's role, this allocation calls into question if features with shared human-system performance are capable of fitting into a clearly prescribed level within existent taxonomies (Seppelt, Reimer, Angell, & Seaman, 2017). Level 2 driving automation provides the greatest opportunity for human-machine overlap and user misunderstanding. The boundaries of the driver assistance system can shift based on the user's perception of the operating mode(s) of the driving automation system and the subtasks of the DDT that the user is required to perform versus those of the driving automation system (see SAE J3114 section 6.2, note 1 (2016b)). This is the time where the user's role should be explained with the least ambiguity, and unfortunately, that has not been the case.

Training materials for driving automation systems generally take a machine oriented and operational focus and neglect to communicate the operator's role in using automated systems effectively. For example, operator's manuals elect to inform users of system limitations, operating

conditions, and other system performance based criteria. However, if automation is to be used appropriately, potential biases and influences should be recognized by professionals (developers, training personnel, managers) and communicated to users (Parasuraman & Riley, 1997). Manual designers have not yet capitalized on the opportunity to enlighten the prospective operator about how prolonged use of these systems may affect them (fatigue, complacency, bias, etc.).

In her classic examination, *Ironies of Automation,* Bainbridge (1983) recognized the issues ahead for the human operators in an increasingly automated world. She stated, "*Perhaps the final irony is that it is the most successful automated systems, with rare need for manual intervention, which may need the greatest investment in human operator training… It is inadequate to expect the operator to react to unfamiliar events solely by consulting operating procedures."*

Several methods that were used by consumers to learn how to use their in-vehicle technologies were identified by Abraham, Reimer, Seppelt, Fitzgerald, & Coughlin (2017); the most prevalent among them were trial-and-error (53%). consulting the vehicle owner's manual (55%), and learning from the dealership (42%). However, many shortcomings have been identified with these common training methods including the accuracy of the information (Abraham, McAnulty, Mehler, & Reimer, 2017), completeness of material covered (Leonard, 2001) , and one's ability to judge their own performance (Kruger & Dunning, 1999; Kyriakidis, Happee, & de Winter, 2015; Llaneras, 2006). The driver's performance requirements in terms of OEDR completion have been clearly specified by the SAE Levels of Automation. It is essential to understand if there are gaps between the specified standard and the observed behavior. In the event of a misalignment in demand and capability, strategies for closing and eliminating the gap (training or system re-design) should be put forth.

Summary and key research gaps

This literature review has demonstrated that the introduction of more advanced driving automation systems fundamentally changes the driving task for the human operator. Changes in task demands may lead to drivers engaging in behaviors that exceed the operational capabilities of the automated system (Kinnear & Helman, 2013), and inadequate completion of the OEDR subtask. Initial poor choice of behavior on the part of the driver may be exacerbated by the fact that current users of advanced vehicle systems have demonstrated an incomplete understanding of system capabilities and limitations (McDonald, Carney, & McGehee, 2018b; McDonald et al., 2015, 2016, 2017) resulting in continued misuse or disuse of these features.

New vehicles have more active safety features and crash prevention measures, consequently we may observe a reduction in the number of crashes observed despite increased risk taking behaviors. As drivers continue to become more familiar with their assistance systems, averse behavioral adaptation may occur due to a lack of consequences (positive punishers). However, when systems fail if drivers are not prepared to take control of the vehicle and do not have the adequate knowledge to know to do so, the likelihood of crash involvement increases. Driver training may help mitigate some of the maladaptive behaviors associated with increased perceived familiarity with vehicle automation. However to adequately develop training we must understand the current state of driver training for vehicle technologies, the conditions under which drivers choose to use their vehicle systems, and driver interaction with these systems over time.

Research Questions & Dissertation Overview

The primary goal of this dissertation is to investigate drivers' behavioral adaptation to partially automated driver assistance systems and identify training strategies which could effectively stave off the negative effects of behavioral adaptation. In particular, this dissertation

seeks to address the following questions through a series of three studies:

Chapter 2. Driver Training for Automated Vehicle Technology Knowledge, Behaviors, and Attitudes

1. Does participant knowledge of driving automation vary by training type, age group, or exposure to driving automation systems?
2. Is there a difference in eye glance behavior between training protocols and driver age group by automation state or exposure to driving automation systems?
3. Does participant hand placement relative to the vehicle controls vary by training type, age, automation system status, or exposure to driving automation systems?
4. Does participant attitude toward vehicle automation vary by training type, age group, or exposure to driving automation systems?
5. Does participant perception of training vary by training type or participant age group?

Chapter 3. A Naturalistic Evaluation of Driver Behavior Using Driving Automation Systems

1. What percentage of driving exposure is assisted by ACC+LKAS (driving automation systems)? How does this vary by driver, vehicle, and temporal characteristics?
2. Under what conditions are drivers most likely to activate ACC+LKAS?
3. What is the frequency and duration of off road glances when ACC+LKAS are active compared to when they are inactive?
4. Is driver monitoring of the instrument panel different during assisted driving compared to unassisted driving?
5. Are drivers more likely to engage in high-risk secondary tasks when level 2 systems are active compared to when they are available?

Chapter 4. Behavioral Adaptation with Driving Automation at Early Exposure

1. How does driver's mean and minimum time-gap change as a function of automated system use (exposure)?
2. Do drivers adjust their adaptive cruise control distance setting with increased exposure to driving automation?
3. What is the frequency and duration of off road glances when level 2 systems are active compared to when they are not? How do the frequency and duration of off road glances change with exposure to the driving automation systems?
4. What is the frequency and duration of instrument panel glances when level 2 systems are active compared to when they are not? Does the frequency and duration of driver glances to the instrument panel change with increased level 2 system exposure compared to unassisted driving?
5. Is there a difference in the prevalence and likelihood of secondary task engagement while the driving automation systems are active compared to when they are inactive? How exposure to the driving automation influence driver secondary task engagement?

Chapter 2. Driver Training for Automated Vehicle Technology Knowledge, Behaviors, and Attitudes

This chapter presents an examination of the relationship between mode of training presentation and driver knowledge, behavior, and attitudes toward driving automation systems. The present study examines whether a different training method results in observable differences in driver knowledge, behavior, and perception toward driving automation systems. This study was conducted on a closed test track with 40 participants where each participant completed one of two types of training protocol. Following completion of the training, participants were escorted to the closed test track where a variety of driving scenarios were completed.

Research Objectives

The main objectives of this research are as follows:

1. To determine if there is a difference in knowledge and/or driving performance between drivers who are permitted time to self-study an operator's manual and those who experience a multimedia training protocol.
2. To develop recommendations regarding the future need of training for automated vehicle systems.

In order to demonstrate the differences in training type, it is important to conduct knowledge and skills assessments of participants in a closed-test track environment. This study aims to lay groundwork for recommendations on training for driver assistance systems in the future, by assessing driver skills and knowledge in a controlled risk environment.

Research Questions

The following research questions from the topic areas of user knowledge, driving behavior, attitudes, and perception of training will assist in guiding this study:

Knowledge

RQ 1. Does participant knowledge of driving automation vary by training type, age group, or exposure to driving automation systems?

Driving Behavior

RQ 2. Is there a difference in eye glance behavior between training protocols and driver age group by automation state or exposure to driving automation systems?

RQ 3. Does participant hand placement relative to the vehicle controls vary by training type, age, automation system status, or exposure to driving automation systems?

Attitude toward Vehicle Automation

RQ 4. Does participant attitude toward vehicle automation vary by training type, age group, or exposure to driving automation systems?

Perception of Training

RQ 5. Does participant perception of training vary by training type or participant age group?

Hypotheses

It is hypothesized that participants who complete the multimedia training will have a better understanding of the driving automation system than drivers who complete the conventional training protocol. It is also anticipated that younger drivers will perform better on knowledge tests and that participant performance on these tests will improve after driving the test vehicle and using the driving automation system.

It is anticipated that drivers who complete the multimedia training will have shorter glances away from the forward roadway while using the driving automation system. Younger drivers are expected to have higher eyes off road time than mature drivers while automation is active

compared to when it is inactive. It is also expected that driver glances away from the forward roadway will increase with increased exposure to the driving automation systems and that drivers will be more likely to have their hands away from the steering controls whilst the driving automation system is in use compared to when it is inactive.

It is hypothesized that participants will have a slightly favorable view toward both forms of training in terms of relevance of content, time to complete, etc. but participants will find driving the vehicle or the combination of training and experience with the vehicle most helpful in preparing them for using the driving automation. It is anticipated that very few participants, if any will find the training in isolation beneficial to their understanding of the automated vehicle system.

Methods

To answer the research questions posed, a comparative evaluation of training protocols and driver performance parameters was conducted on the Virginia Smart Road. A variety of analyses (descriptive and inferential statistics) were employed to assess the aforementioned research questions, which are restated below. For all analyses, statistical significance was evaluated at $\alpha = 0.05$.

Participants

Forty participants from southwestern Virginia volunteered for this research effort, the two target age ranges for volunteers were 18 to 25 years old and 55 to 75 years old (Table 2). All participants were pre-screened for general health and driving experience during initial phone interviews. Participants who owned a primary vehicle that had advanced systems such as adaptive cruise control, lane keeping assist, or automatic emergency braking were not eligible to be participate in the study meaning that participants in this study could be considered generally inexperienced with driving automation systems.

On the day of the scheduled experimental trials, participants were given a brief overview of the purpose of the study and affirmed their consent using the approved Virginia Tech Institutional Review Board (IRB) human subjects consent form (Appendix B. Chapter 2: Driver Training for Automated Vehicle Technology Informed Consent). A Snellen eye test (corrected visual acuity of 20/40 or better) and basic hearing test were administered; all participants passed the pre-drive test. The study session consisted of one two-hour visit; participants were compensated $60.00 for their time.

Table 2. Participant demographics and training group assignment

	Conventional Training	**Multimedia Training**	**Total**
Younger Participants (18 – 25)	10 *(M=21.4, SD=1.58)*	10 *(M=21.1, SD=1.37)*	20 *(M=21.25, SD=1.45)*
Older Participants (55 – 75)	10 *(M=59.7, SD=5.64)*	10 *(M=66.2, SD=7.63)*	20 *(M=62.95, SD=7.33)*
Total	20 *(M=40.55, SD=20.06)*	20 *(M=43.65, SD=23.74)*	40 *(M=42.1, SD=21.75)*

ApparatusParticipants were randomly assigned to one of two training groups prior to their arrival for the experimental session. Training modules were completed in the parked research vehicle, without the experimenter present. The research vehicle for this study was a 2016 Tesla Model S with Autopilot Software v8.1.

A data acquisition system (DAS) was used to record all relevant kinematic driver performance data. The DAS was located out of participant view in an unobtrusive location. DAS hardware was wired to interface with the vehicle through Controller Area Network (CAN) protocols accessed by the Onboard Diagnostic II (OBD II) port and collected and recorded data streams asynchronously, allowing each sensor to operate at its optimal collection rate. The DAS recorded at millisecond precision at the rate native to each sensor or CAN variable.

Five camera views were collected while participants were in the research vehicle (Figure 3). The camera views included a view of the forward roadway, over-the-shoulder, the participant's

face, the foot well/pedal, and the instrument panel. Data collected from the camera views were used in subsequent eye glance analyses and participant driving behavior analyses.

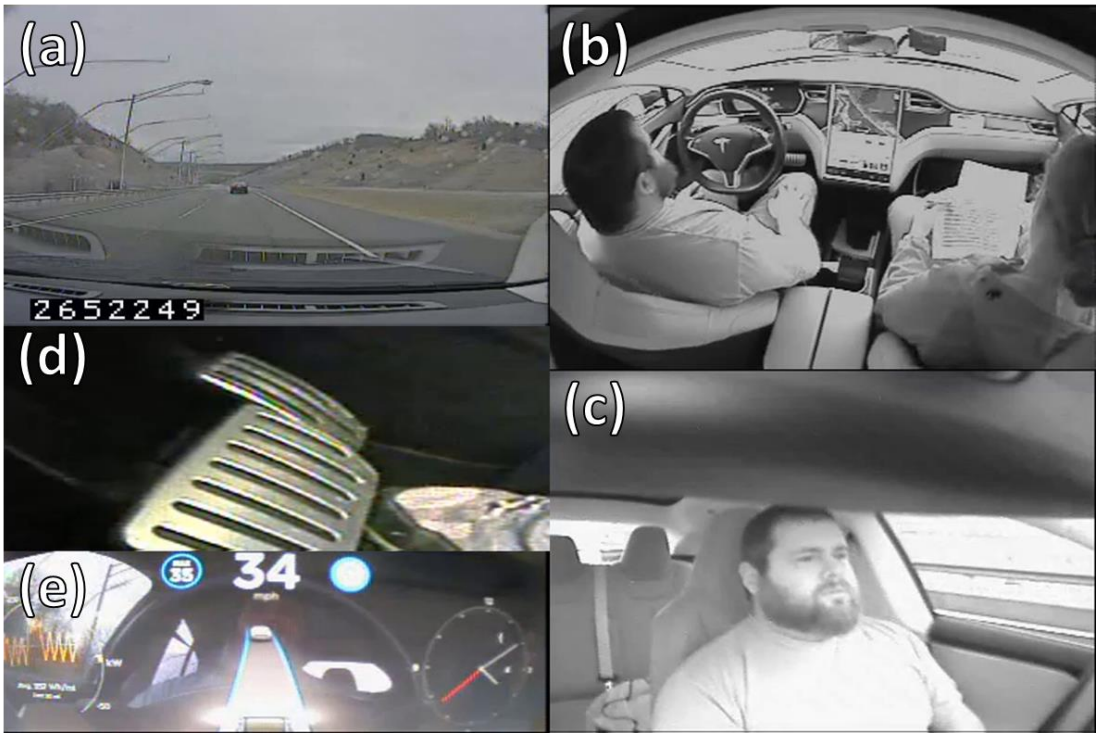


Figure 3. Camera views used while participants were in the research vehicle included: a) forward roadway, b) over-the-shoulder, c) participant face, d) foot well/pedal, e) instrument panel

Procedure

The experimental session was divided into five distinct sections; pre-training, training, post-training, test track drive, and post-drive (Figure 4). The sequence of events was the same for all participants and all events were completed in the same experimental session.

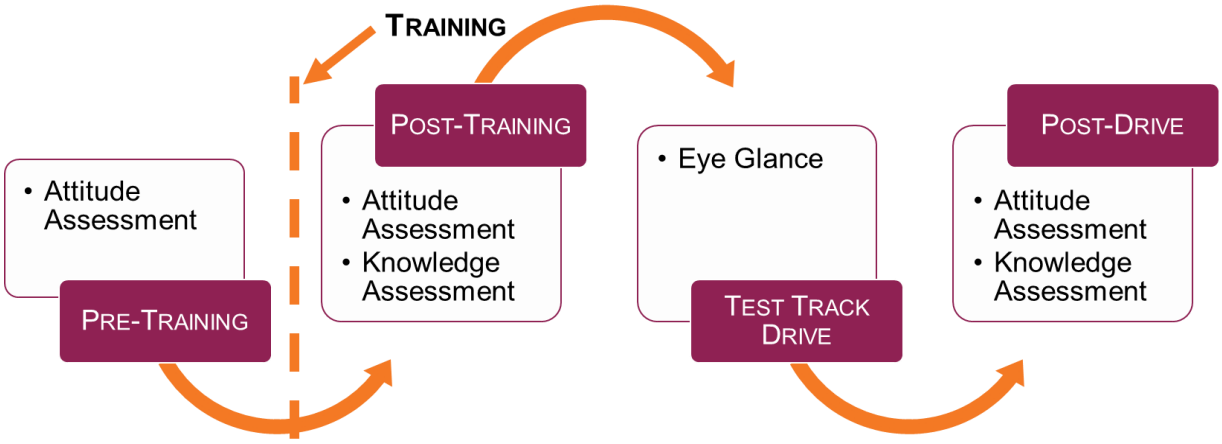


Figure 4. Sequence of study experiences

Pre-Training, Post-Training, and Post-Drive Questionnaires. Knowledge and attitude questionnaires were administered at three points in the study. Open response knowledge questions about adaptive cruise control and lane keeping assistance systems were asked in the pre-training, post-training, and post-drive phase of the study. Drivers were permitted to freely respond to "what the system does" and "how the system works". During the same three points in the study, participants completed a trust in automation questionnaire.

Participants completed the multiple selection knowledge questionnaires after finishing their assigned training protocol and after driving the vehicle (post-training and post-drive). Participant response to questions was marked as correct or incorrect—no partial credit was given. Questions covered three knowledge areas: operational design domain, system limitations, and system components.

Training. After completing the intake procedure and questionnaires, participants were escorted to the research vehicle where they completed their randomly assigned protocols after a brief orientation to the vehicle. Participants in both the control and experimental groups received information regarding automated system components and system purpose, function, and limitations. The training program covered specific topics from the Tesla Model S operator's

manual (Appendix A. Driver Training for Automated Vehicle Technology Training Topics)

Participants were left to complete the training in the vehicle alone while the researcher "completed tasks" (e.g., organizing study paperwork, reviewing protocols, etc.) outside of the vehicle for the on-road portion of the study. The researcher informed the participant that they may seek assistance if they experience technical difficulties (for example, the screen goes blank or they exit the training and cannot re-enter), but any questions regarding the vehicle technologies were held until all stages of the study were complete. When the training was complete the participants signaled that they were finished with the training by waving at the researcher or honking the horn.

Conventional Training Protocol (Control Group). The control group received training on how to use driver assistance systems (i.e., Traffic Aware Cruise Control and Autosteer) by reading the specified section of the operator's manual. The goal was to provide participants with an experience similar to how much of the motoring public learns to use in-vehicle technologies when purchasing a new vehicle from a manufacturer. The conventional training home screen was visible on the on an electronic touch screen display mounted over the stock center stack display (Figure 5). The mean training duration for participants completing this training protocol was approximately 16 and a half minutes (M=16:25, SD = 4:57).

Figure 5. The owner's manual for the Tesla was displayed on a touchscreen display mounted over the stock center stack of the vehicle.

Multimedia Training Protocol (Experimental Group). The experimental group received training via an interactive multimedia module, which was divided into three distinct components (Overview, Traffic-Aware Cruise Control, Autosteer). As part of the training, the video instructed participants to manipulate controls and interact with the system in order to promote an active learning component of the training. The experimental training interface consisted of two screens, one over the stock center stack display and one placed over the steering wheel to imitate the instrument panel displays (Figure 6). The mean training duration for participants completing this training protocol was approximately 19 minutes (M=19:13, SD = 1:17).

Figure 6. Tesla interior from driver's perspective. A mounted touchscreen display overlaid the stock center stack display to host the training modules (A). A custom

instrument cluster display replicated the icons and system states with the training modules using the timing from the training (B).

Test Track Drive. After completion of the training protocol, participants were escorted to the Virginia Smart Road where the test track drive portion of the study took place. Participants completed six laps on the Smart Road and were instructed to stop the vehicle at a specified point for questions and additional instructions. A VTTI researcher was in the front seat during the test track portion of this study. A confederate vehicle, driven by a VTTI researcher, accompanied the research vehicle on to the Smart Road. Participants were instructed that the maximum speed limit for the study was 35 mph, they should maintain their current lane, maintain a two-second following distance when there is a vehicle in front of them, and obey all traffic laws.

Research Environment. The Virginia Smart Road is a closed-access, two-lane roadway built to Federal Highway specifications and located at the Virginia Tech Transportation Institute (VTTI). This study used a section of the Smart Road that was approximately one mile long. Secondary tasks were completed continuously on two 0.3 mile sections of the Smart Road bisected by a 0.3 mile transition area (Figure 7). While in the transition area secondary tasks were not to be continued and the confederate lead vehicle drove at a constant speed in front of the subject vehicle.

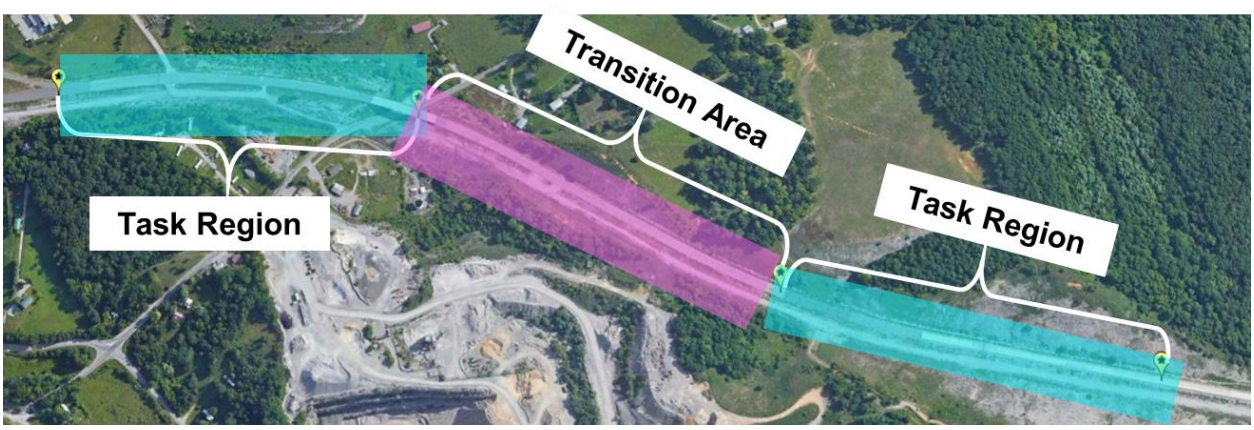


Figure 7. A one mile segment of the Smart Road Highway was divided into three parts. Two×0.3 mile task regions and one×0.3 mile transition area. While in the task regions

drivers completed secondary tasks while driving in the transition area drivers were not permitted to perform secondary tasks and the confederate lead vehicle drove at a constant speed in front of the subject vehicle.

Secondary Task Descriptions. After completing the initial two baseline laps, participants were asked to engage in secondary tasks (Table 3). The duration of the secondary task activity spanned the length of the secondary task region (approximately 30 seconds). Secondary task involvement was aggregated into two levels;

- Task: Participants were actively performing secondary tasks during this trial.
- No Task: Participants were not performing secondary tasks during this trial.

Table 3. Smart Road Experimental Design

Lap	Automation	Task
1	Off	None
2	On	None
3	On	Task
4	Off	Task
5	On	Task
6	Off	Task

Independent Factors

The independent factors used in this study are described in Table 4.

Table 4. Study 1 independent variables and descriptions

Independent Variables	Definition & Levels
Age Group (Between-Subjects)	Depending on subject age on day of experimental visit participants were recruited from one of two categories. • Younger: 18 – 25 years old • Mature: 55 – 75 years old
Training (Between-Subjects)	Participants were randomly assigned to one of two training groups prior to their arrival for the experimental session. A detailed description of the training protocols are provided on page 31. • Conventional: Control group, receiving training by reading the operator's manual • Multimedia: Experimental group, completed multimedia training
Automation (Within-Subjects)	Automation state is a binary indicator of whether the human operator or the driving automation system has active control of the vehicle's lateral and longitudinal motion. During half of the laps of the test track session, participants were asked to activate the automated systems. • ON: Driving automation system has active control of vehicle's lateral and longitudinal motion. • OFF: Human operator has active control of vehicle's lateral and longitudinal motion.
Secondary Task (Within-Subjects)	After completing the initial baseline laps, participants were asked to engage in secondary tasks. • No Task: Participants were not completing secondary tasks • Task: Participants were continuously performing visual or visual manual tasks.
Exposure Period (Within-Subjects)	Measure of participant exposure to the automated system, each exposure period consisted of one lap with automation on and one lap with automation off. • Early: Laps 1 & 2 • Middle: Laps 3 & 4 • Late: Laps 5 & 6
Admin Time (Within-Subjects)	Questionnaires were administered to participants at specific points during the study. • Pre-Training: Response given prior to receiving training • Post-Training: Response immediately after receiving training • Post-Drive: Response after receiving training and driving the research vehicle

Dependent Measures

The dependent measures used in this study for the analyses shown in Table 7 are discussed below. The primary objective areas include: driver knowledge of driving automation systems, driver behavior while using driving automation, driver attitudes toward the systems and the driver's perception of the training program that they received.

Driving Automation Knowledge. Participants completed a multiple selection knowledge questionnaire at two points during the study. The first time was immediately after completing their assigned training protocol (post-training), the second time was after driving the vehicle on the closed test track (post-drive). Participant responses to questions was marked as correct or incorrect, there was no partial credit given. Questions covered three knowledge areas: operational design domain, system limitations, and system components.

Driving Behavior. Participant behavior during instances of assisted and unassisted driving was assessed. Driver eye glance behavior and hand placement are considered under this objective.

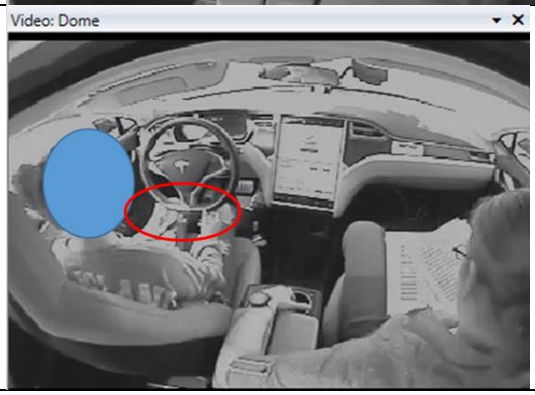
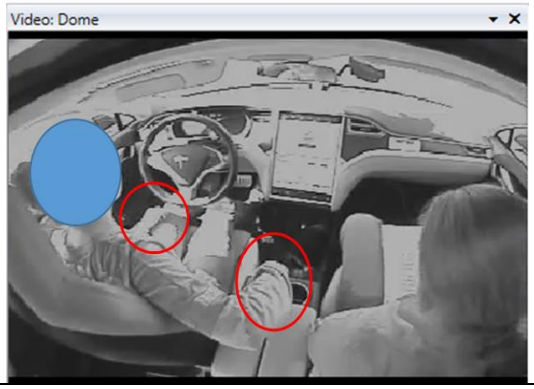
Eye Glance Behavior. Trained data reductionists manually coded participants' glances for each frame of the specified secondary task events and pre-determined baseline and transition scenarios. These epochs were approximately 30 seconds in duration. Off road glance locations consisted of glances to any area other than the forward roadway. Four measures of eye glance behavior were used in this study: single longest off road glance, mean off road glance duration, number of off road glances, and percent total eyes off road time. These measures are described in Table 5.

Table 5. Test Track Study Eye Glance Measures

Glance Measure	Acronym	Description
Total Eyes off Road Time	TEORT	Total Eyes off Road Time (TEORT) is the summation of all glance durations to all AOIs other than the road scene ahead during a sample interval in seconds (SAE International, 2017).
Single Longest off Road Glance	SLG	The single longest off road glance (SLG) is the duration of the single longest glance away from the forward roadway during the sample interval.
Mean Off Road Glance Duration	MGOR	The mean glance off road is the average duration of all off road glances during the 30-second sample interval.
Number of off Road Glances	NORG	This measure it the average number of glances away from the forward roadway during the 30-second sample interval.

Hand placement during transitions. Participant hand placement during transition events was measured during four epochs when the automated systems we active and inactive and at early and late periods in the study. Three points in time were randomly sampled from the beginning, middle, and ending thirds of each transition epoch. Trained data reductionists manually coded the location of the participant's left and right hand with respect to the steering wheel. The locations coded are shown in Table 6.

Table 6. Hand placement coding and exemplar placements

Hand Placement Coding	Example from Video
On the wheel	
Hover/Fingertip Hover defined as within an inch or two from the wheel and poised to take control at any moment	
Off Wheel	

Attitude toward Driving Automation. The trust scale used in this study was a six item trust scale proposed by Vasquez et al. (2015). Responses to statements used a 7-point Likert-type scale with options ranging from “1” (strongly disagree) to “7” (strongly agree).

Perception of Training (Perceived Value). Participant’s perception of the value of training with respect to how prepared they felt to operate the vehicle using the driver assistance systems was assessed using a battery of questions. Participants indicated their level of agreement

with statements about the clarity of training objectives, degree of participation, relevance of training topics, organization of training topics, and the utility of the training using a seven point Likert scale. Upon completion of the test track drive participants were also asked to indicate which they felt was most useful to their understanding of the automated vehicle system. Participants were able to choose from one of four options; the training, driving the vehicle, both were equally helpful, both were equally unhelpful.

Analyses

Statistical significance was evaluated at $\alpha = 0.05$, where appropriate, effect sizes were determined and reported using partial eta-squared (η_p^2). Where relevant, post hoc analyses were performed using Tukey's honest significant difference (HSD) for main effects and simple effects testing for interaction effects.

To investigate driver knowledge of driving automation systems logistic regression was used to estimate odds ratios of correct response by each main effect for: age (younger, mature), training protocol (conventional, multimedia), and administration period (post-training, post-drive).

Participant driving performance was investigated using a variety of measures and methods. General linear models were used to investigate operator behavior under secondary task conditions and during transitions. Epochs in which participants were marked as attempting the secondary task when prompted were included in this analysis. The effects of age (younger, mature) and training (conventional, multimedia) were examined as between subjects factors and automation (on, off), and secondary task (task, no task) were examined as within subjects factors. Similarly, participant eye glance measures were assessed during the transition period to determine if driving behavior changes with over time. The effects of age (younger, mature) and training (conventional, multimedia) were examined as between subjects factors and automation (on, off), and exposure

time (early, late) were examined as within subjects factors.

A binary logistic regression was used to determine the likelihood of participant hand location during transitions (on the wheel or off the wheel). Age (younger, mature) and training (conventional, multimedia) were examined as between subjects factors and automation (on, off), and exposure time (early, late) were examined as within subjects factors.

General linear models were used to assess participant attitudes toward driving automation for the effects of age (younger, mature) and training (conventional, multimedia) as between subjects factors and Admin Time (pre-training, post-training, post-drive) as a within subjects factors. Finally, participant perception of the training was analyzed using summary statistics.

Table 7. Overview of research questions and associated independent/dependent variables

Objective	Sample[1]	Research Question	Dependent Vars.	Independent Vars.	Analysis
Knowledge	Q	Does participant knowledge of level 2 driving automation vary between training type, age group, or time?	Correct/Incorrect response (binary)	Age Group Training Admin Time	Logistic Regression
Behavior	SR	What is the difference in participant eye glance behavior between training protocols and driver age group by automation state and secondary task engagement?	SLG MGOR Percent EORT N Glances	Age Group Training Automation Secondary Task	GLM
Behavior	SR	What is the difference in participant eye glance behavior between training protocols and driver age group by automation state and exposure time to the driving automation system?	SLG MGOR Percent EORT N Glances	Age Group Training Automation Exp Time	GLM
Behavior	SR	Does participant hand placement relative to the vehicle controls vary by training type, age, automation system status, or time?	Hands On/Off the Wheel	Age Group Training Automation Exp Time	Logistic Regression
Attitude toward VA	Q	Does participant attitude toward vehicle automation vary by training type, age group, or time?	1 – 7 (Likert Scale)	Age Group Training Automation Exp Time	GLM
Perception of Training	Q	Does participant perception of training vary by training type or participant age group?	1 – 7 (Likert Scale)	Age Group Training	Descriptive Statistics

[1] Q: Questionnaire; SR: Smart Road

Results

Driving Automation Knowledge Operational Design Domain. Drivers in the mature age group were 2.89 times as likely to correctly identify when it would be appropriate to use ACC compared to drivers in the younger age group (OR: 2.89, [CI:1.06, 7.92]). Drivers in the mature age group were 3.35 times as likely to correctly identify when it would be appropriate to use lane keeping assist (LKA) compared to drivers in the younger age group (OR: 3.35, [CI:1.2, 9.4]).

System Limitations. For ACC, only four participants post-training and two participants post-drive were able to identify all situations where ACC may not work as expected. Similarly, for lane keeping, participants were unable to identify all situations where the system may not work as expected. Only one driver in both the post-training and post-drive questionnaires responded correctly.

When looking at the participant's disaggregated responses to the limitations their correct responses for correlated limitations were quite high. For example, participants were easily able to recall the heavy rain and snow limitation and the sensor obstruction limitation. Participants recalled the heavy rain and snow limitation with 100% accuracy on the post-training and post-drive assessments for ACC, and with 95% accuracy with LKA. Participants also did very well with the "sensors are obstructed" limitation for both technologies in the post-training and post-drive tests. Remarkably, the sensors obstructed limitation did not extend to the dusk and dawn limitation for either systems in which the optical sensor will struggle to detect forward vehicles given the angle of the sun. Additionally participants struggled to recall the extremely hot/cold temperature limitations for both technologies with the group performing no better than 40% for those limitation on either post-training or post-drive test.

Interestingly, for ACC, participants struggled to recall the windy road limitation during

both tests and performed worse on the assessment administered post-drive (70%) than on the one given post-training (78%). For LKA, participants were able to recall the absence or lack of quality lane markings being a limitation of these systems. However this did not translate to the work zone where no more than 78% of participants were able to identify work zones as a limitation of LKA. This is possibly due to the diverse nature of the work zone environment which does not necessarily always include obscured or missing lane markings.

Table 8. Participant responses to the limitation questions where "PT" indicates "Post-Training", "PD" indicates "Post-Drive" and "PD-PT" is the change in score between Post-Training and Post-Drive.
Green rows are limitations that were identified in the training program.

ACC			
Limitation Response	**PT**	**PD**	**PD-PT**
Extremely hot or cold temperatures	37.5%	30.0%	-7.5%
Clear sunny days	15.0%	12.5%	-2.5%
Dusk and dawn	37.5%	42.5%	5.0%
Heavy rain or snow	100.0%	100.0%	0.0%
Poor tire traction	72.5%	72.5%	0.0%
Sensors are obstructed	100.0%	97.5%	-2.5%
Windy roads	77.5%	70.0%	-7.5%
Straight roads	0.0%	0.0%	0.0%
Roads with poor lane markings	35.0%	27.5%	-7.5%
Roads with no lane markings	32.5%	27.5%	-5.0%
Roads with clearly visible lane markings	0.0%	2.5%	2.5%
Work Zones	75.0%	70.0%	-5.0%
Toll plazas	75.0%	65.0%	-10.0%
LKA			
Limitation Response	**PT**	**PD**	**PD-PT**
Extremely hot or cold temperatures	27.5%	27.5%	0.0%
Clear sunny days	2.5%	15.0%	12.5%
Dusk and dawn	40.0%	37.5%	-2.5%
Heavy rain or snow	95.0%	95.0%	0.0%
Poor tire traction	45.0%	65.0%	20.0%
Sensors are obstructed	97.5%	100.0%	2.5%
Windy roads	65.0%	67.5%	2.5%
Straight roads	15.0%	0.0%	-15.0%
Roads with poor lane markings	87.5%	90.0%	2.5%
Roads with no lane markings	87.5%	92.5%	5.0%
Roads with clearly visible lane markings	5.0%	2.5%	-2.5%

Work Zones	77.5%	75.0%	-2.5%
Toll plazas	72.5%	70.0%	-2.5%

System components. For ACC, no main effects were significant. Approximately 80% of subjects were able to correctly identify the forward-looking camera and radar as essential components of the ACC system after training (76% overall). When asked about the LKA system, there was a significant difference in the training effect. Participants who received multimedia training correctly reported all sensors required for system function as specified by the training nearly three times as often as those who received conventional training [OR=2.97, CI: 1.08, 8.23].

Eye Glance Behavior

Linear mixed models were used to investigate operator behavior under secondary task conditions and transitions. Epochs in which participants were marked as attempting the secondary task when prompted were included in this analysis.

During Secondary Task Engagement. Participant eye glance behavior was assessed using the following independent factors; age (Younger, Mature), training protocol (Conventional, Multimedia), automation (On, Off), and secondary task (Task, No Task).

Single Longest Glance off Road. Automation was found to have a significant effect on the single longest off road glance duration [$F(1,110)=20.02$, $p<.0001$, $\eta_p^2=0.154$]. When the Autosteer systems were actively controlling the vehicle, the single longest glance away from the forward roadway was greater (M= 2.21, SD= 1.78) than when the driving automation systems were inactive (M= 1.69, SD= 1.04). The interaction between age and secondary task had a significant main effect on the single longest glance duration [$F(1,110)=8.63$, $p=0.004$, $\eta_p^2=0.073$] . Younger drivers had significantly longer single longest glances when performing secondary tasks (M=2.90, SD=2.03) compared to when they were not performing secondary tasks (M=1.78, SD=0.73). Mature drivers looked away from the road significantly longer when they were performing

secondary tasks (M=2.60, SD=1.44) compared to when they were not performing secondary tasks (M=1.54, SD=0.89).

Mean off Road Glance Duration. The main effect of automation status was found to significantly affect the mean off road glance duration [F (1,110)=24.79, p<.0001, η_p^2=0.184]. The mean off road glance duration was 1.04 seconds while the automated systems were active (M=1.04, SD=0.67), and was 0.82 seconds (M=0.82, SD=0.46) while the systems were inactive.

There was a three-way interaction between age, automation, and secondary task for mean off road glance duration [F (1,110)=5.12, p=0.0256, η_p^2=0.045] (Figure 8). Mature drivers showed no difference in mean glance duration when completing secondary tasks regardless of whether the vehicle automation was active (M=1.25, SD=0.72) or inactive (M=1.21, SD=0.47). However, younger participants' mean off road glance duration was approximately a half a second longer during secondary tasks when systems were active (M=1.53, SD=0.87) compared to when systems were inactive (M=1.09, SD=0.42).

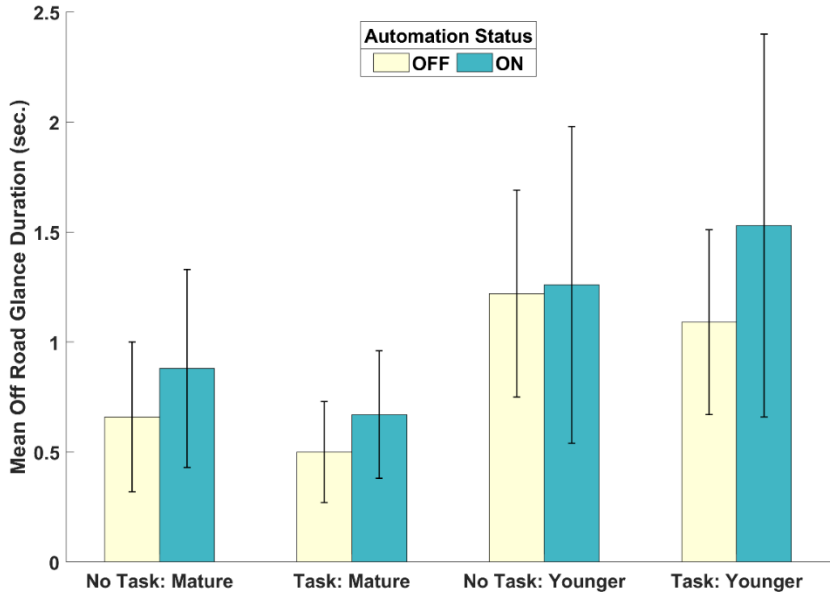


Figure 8. There was a significant interaction between age, automation, and secondary task for mean off road glance duration (standard deviation shown with error bars).

Number of off Road Glances. The main effect of automation had a significant effect on number of glances away from the forward roadway [F (1,110)=6.05, p=0.0155, η_p^2=0.052]. Participants took 1.5 more glances away from the road when the vehicle automation was off (M=12.05, SD=6.65) compared to when it was on (M=10.9, SD=5.16). There was a significant interaction between automation and secondary task [F (1,110)=12.21, p=0.0007, η_p^2=0.099] for the number of glances away from the forward roadway (Figure 9).

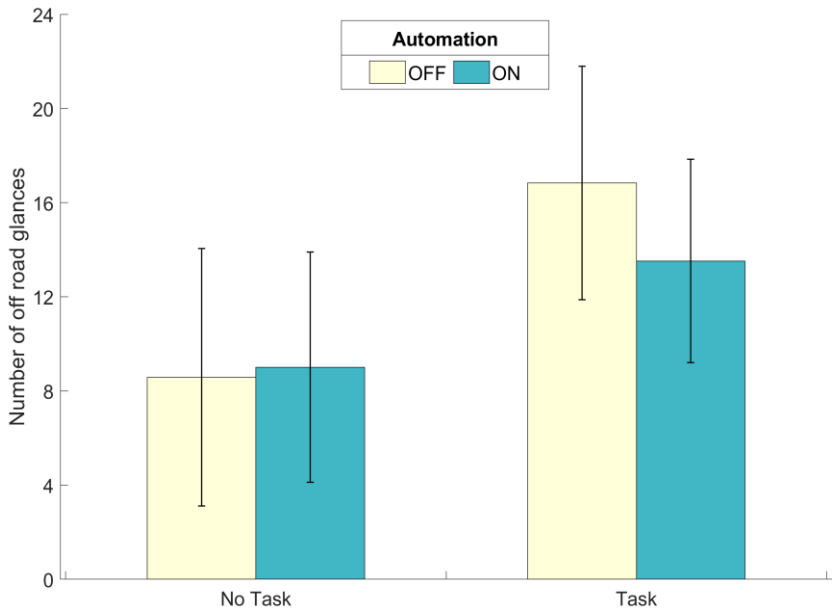


Figure 9. There was a significant interaction between automation and secondary task for the number of glances away from the forward roadway (standard deviation shown with error bars).

No differences in number of off road glances were observed when participants were not performing secondary tasks regardless of automation status (No task: M_{OFF}=8.58, SD_{OFF}=5.47; M_{ON}=9.01, SD_{ON}=4.89). However, when performing secondary tasks, participants took significantly more glances away from the road. When the automated systems were active and participants were performing secondary tasks, the number of off road glances was lower (M=13.52, SD=4.32) than when they were completing secondary tasks and the systems were inactive (M=16.83, SD=4.96).

Drivers took short, frequent glances away from the forward roadway when not using the driving automation features. When driving automation was active, glances away from the forward roadway increased in duration.

Percent Total Eyes off Road Time. The percent of time drivers spent looking away from the forward roadway was significantly impacted by secondary task engagement [F (1,110) =666.87, p<.0001, η_p^2=0.858]. Participants who were completing secondary tasks spent an average of 53% (M=52.7%, SD=20.8%) of the task epoch looking away from the forward roadway. When participants were not completing secondary tasks, their percentage of TEORT was only 18% (M=18.0%, SD=12.9%).

While the status of the vehicle automation and secondary task engagement were found to contribute significantly to the percentage of TEORT [F (1,110) =6.8, p=0.0104, η_p^2=0.058], post hoc testing revealed that there was no significant difference between the conditions of secondary task engagement while the automated systems were active (M=51.2%, SD=21.8%) compared to when they were inactive (M=54.2%, SD=19.8%). Participant age group and secondary task engagement contributed to percentage of TEORT [F (1,110) =12.38, p=0.0006, η_p^2 =0.101]. There was no difference in the percentage TEORT between younger and mature participants when no secondary tasks were being performed

During Transitions. Eye glance analysis during transitions took place during the downhill segments of the first and last two laps on the Smart Road. During transitions, no secondary tasks were performed and the confederate lead vehicle drove at a constant speed in front of the subject vehicle, all transition epochs were approximately 30 seconds long (M=30.53, SD=1.02). The independent factors used to asses eye glance behavior during transitions were age (Younger,

Mature), training protocol (Conventional, Multimedia), automation (On, Off), and exposure period (Early, Late).

Single Longest Glance off Road. Automation state had a significant main effect on single longest glance duration [F (1,106) =8.7, p=0.0039, η_p^2=0.073]. Participants had higher glance durations when automation was on (M=1.42, SD=0.68) compared to automation off (M =1.16, SD=0.72). Automation status and exposure time interactively influenced single longest glance duration, [F (1,106)=4.19, p=0.0432, η_p^2= 0.036]. Post-hoc tests showed that all single longest glance durations were significantly different from the early automation off period (M=0.96, SD=0.52). However, no significant differences were observed between any other combinations of conditions.

Mean off Road Glance Duration. There were age related effects on mean glance duration for transition events [F (1, 36) =9.91, p=0.0033, η_p^2=0.216]. Mature drivers had mean off road glances that were longer (M=0.76, SD=0.31) than those of younger drivers (M= 0.59, SD=0.25).

Automation state also had a significant effect on mean glance duration during transitions [F (1,111) =14.22, p=0.0003, η_p^2 =0.114]. When the automated systems were actively controlling the vehicle mean glance duration was longer (M=0.74, SD=0.29) than when automated systems were inactive (M=0.6, SD=0.28).

Additionally, automation and exposure period had a significant interaction effect on mean glance duration [F (1,111)=13.13, p=0.0004, η_p^2=0.106]. The mean off road glance duration when vehicle automation was off and the exposure period was early was significantly different from all other factor levels (Figure 10).

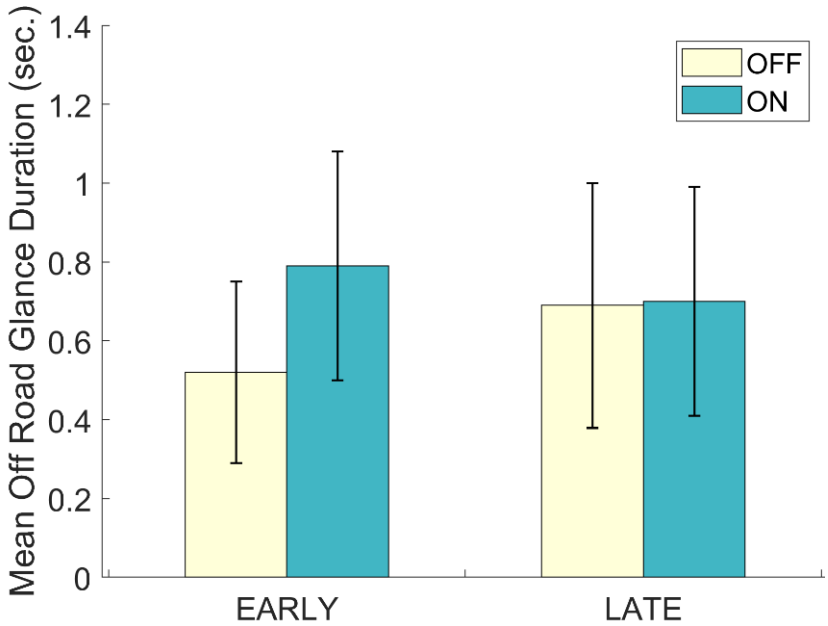


Figure 10. The mean off road glance duration when vehicle automation was off and the exposure period was early was significantly different from all other factor levels.

Number of off Road Glances. The number of off road glances were significantly impacted by training [F (1,36)=7.39, p=0.01, η_p^2=0.1703] and the interaction of training and automation [F (1,106)=7.58, p=0.007, η_p^2=0.064]. However, the post hoc analysis for training × automation revealed that there was no difference in the number of glances away from the forward roadway between groups when the automated systems were active. Participants who received the conventional protocol took an average of 8.75 glances away from the forward roadway (SD=4.50), while participants who partook in the multimedia protocol took 7.56 glance (SD=4.12).

Percent of Total Eyes off Road Time. Exposure time had a significant effect on the percent of time drivers spent looking away from the forward roadway during transition epochs [F (1,111)=4.13, p=0.0454, η_p^2 =0.036]. Participants looked away from the forward roadway longer during the later epochs (M= 20.7%, SD=14.3%) than they did for the earlier epochs (M=17.6%, SD=12.9%).

There was a significant effect with the interaction between training and automation status

[F (1,111)=6.53, p=0.012, η_p^2=0.056]. When the automated systems were inactive, participants who received conventional training (M=22.5%, SD=14.6%) looked away from the forward roadway for a greater percentage of the time than participants who received multimedia training (M=14%, SD=12.6%). While findings are inconclusive by training type, they do indicate that drivers may be more likely to take their eyes away from the forward roadway while automated systems are active the vehicle regardless of secondary task engagement.

Table 9. Percentage of drivers' off road glance duration during transitions by automation status and training type.

Automation	Training	N	Mean	SD	SE	Min	Max
OFF	**Conventional**	40	22.5%	14.6%	2.3%	2.8%	59.7%
	Multimedia	40	14.0%	12.6%	2.0%	0.0%	47.5%
ON	**Conventional**	40	20.3%	11.5%	1.8%	2.5%	53.7%
	Multimedia	40	19.7%	14.7%	2.3%	0.0%	54.0%

Hand Placement Table 10 shows the frequency of driver hand placement relative to the steering wheel while driving through the transition area. Participants were most frequently observed with both hands on the wheel.

Table 10. Participant hand placement relative to the steering wheel while driving through the transition area.

		AUTOMATION	
HAND PLACEMENT	**BINARY HAND PLACEMENT**	**OFF**	**ON**
1 HAND	HANDS ON	63	38
2 HANDS		167	150
HOVER	HANDS OFF	10	35
NO HANDS		0	17

A binary logistic regression was used to determine the likelihood of participant hand location during transitions (on the wheel or off the wheel). The results showed that the automation status contributed to driver's hands being on or off the wheel. Drivers were 11.22 times as likely to have their hands off the steering wheel during transition periods while automation was active compared to when the automation was inactive (OR:11.22, CI: 5.89, 21.36).

Attitude toward driving automation

This questionnaire was used by Vazquez (2015) to assess user trust of an automated driving system. Responses were obtained using 7-point Likert-type scales and internal consistency among statements validated using Cronbach's alpha (Appendix F. Trust Scale IRRs).

I would rely on the vehicle automation to function properly while I am doing something else. Participant age group had a significant effect on participant response to this statement [F (1, 36) = 8.08, p=0.0073, η_p^2=0.183]. Younger participants tended to have a higher numeric response to the reliance on automation to function properly while doing something else (M=4.1, SD=1.8), participants in the mature demographic were less inclined to rely on the vehicle automation to function properly while performing other tasks (M=3.15, SD=1.4).

Participant exposure to the vehicle automation also had a significant effect on participant response, [F (2, 72)=10.58, p <0.0001,η_p^2 =0.227]. There was a significant difference between the responses given in the post-drive questionnaires (M=4.4, SD=1.6) and those given at all other points prior (Pre-Training; M=3.3, SD=1.6; Post-Training; M=3.2, SD=1.5)

I would rely on vehicle automation to provide alerts when needed. No significant effects were found in this analysis. This is likely because participants did not experience any abnormal alerts.

Vehicle automation gives false alerts. Participant exposure to the vehicle automation was found to have a significant effect on participant response [F(2,72)=5.58, p=0.0056, η_p^2 =0.134]. The interaction of exposure period and training was also significant [F(2,72)= 3.82, p=0.0266, η_p^2 =0.096] (Table 11 and Figure 11). While there was no difference between the groups prior to training (M_C=3.7, SD_C=1.2; M_{MM}=3.5, SD_{MM}=0.8), after training, participants who received multimedia training agreed to a greater extent that vehicle automation provides false alerts

(M_{MM}=4.5, SD_{MM}=0.9) compared to participants who received conventional training (M_C=3.8, SD_C=1.2). After experiencing the vehicle automation, participants who received multimedia training seem to regress back toward their initial opinion about vehicle automation providing false alerts. Participants who received conventional training remained relatively unmoved in their opinion on the frequency of false alerts.

Table 11. Participant level of agreement with the statement, "Vehicle automation gives false alerts."

Training	Admin Time	Mean	SD
Conventional	Pre-Training	3.7	1.2
	Post-Training	3.8	1.2
	Post-Drive	3.4	1.3
Multimedia	Pre-Training	3.5	0.8
	Post-Training	4.5	0.9
	Post-Drive	4.1	0.6

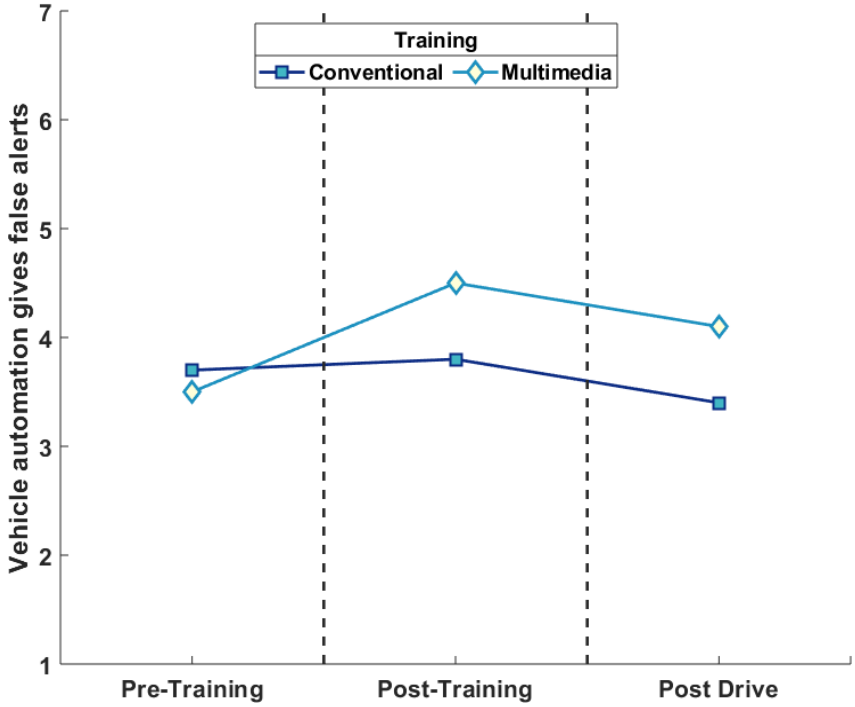


Figure 11. Participants who received the multimedia training agreed to a greater extent in the post-training session to believe that vehicle automation gave false alerts. After experiencing the system both training groups experienced a reduction in their level of agreement from their post-training levels.

Vehicle automation is dependable. Participant's exposure to the automated systems was found to significantly influence participant agreement with the statement "vehicle automation is dependable" [$F(2,72)=4.11$, $p=0.0204$, $\eta_p^2=0.102$]. Post hoc tests indicated that participant responses were significantly different between the post-training ($M=4.48$, $SD=0.85$) and post-drive ($M=4.95$, $SD=1.08$) tests.

I am familiar with vehicle automation. Participant's exposure to the vehicle automation had a significant effect on participants' perceived familiarity with vehicle automation [$F(2, 72) = 31.76$, $p < .0001$, $\eta_p^2 = 0.469$]. Participants agreed to a greater extent with the statement "I am familiar with vehicle automation" after driving the vehicle ($M = 4.95$, $SD = 1.01$) compared to both the pre- ($M = 3.43$, $SD = 1.58$) and post-training ($M = 3.48$, $SD = 1.36$) conditions.

The interaction between participant age and time also had a significant effect on perceived familiarity with vehicle automation [$F(2, 72) = 11.80$, $p < .0001$, $\eta_p^2 = 0.247$] (Figure 12). Mature participants had higher agreement with the statement "I am familiar with vehicle automation" before receiving training ($M = 4.2$, $SD = 1.15$) compared to younger participants ($M = 2.65$, $SD = 1.6$). After receiving training, there was no difference in the responses between the two age groups. Neither group was particularly confident or unconfident ($M_Y = 3.65$, $SD_Y = 1.14$; $M_M = 3.3$, $SD_M = 1.56$). After driving the vehicle, participants' average response increased; there was no difference between the age groups for the post-drive response, and scores were significantly higher than post-training responses ($M_Y = 5.05$, $SD_Y = 1.23$; $M_M = 4.85$, $SD_M = 0.75$).

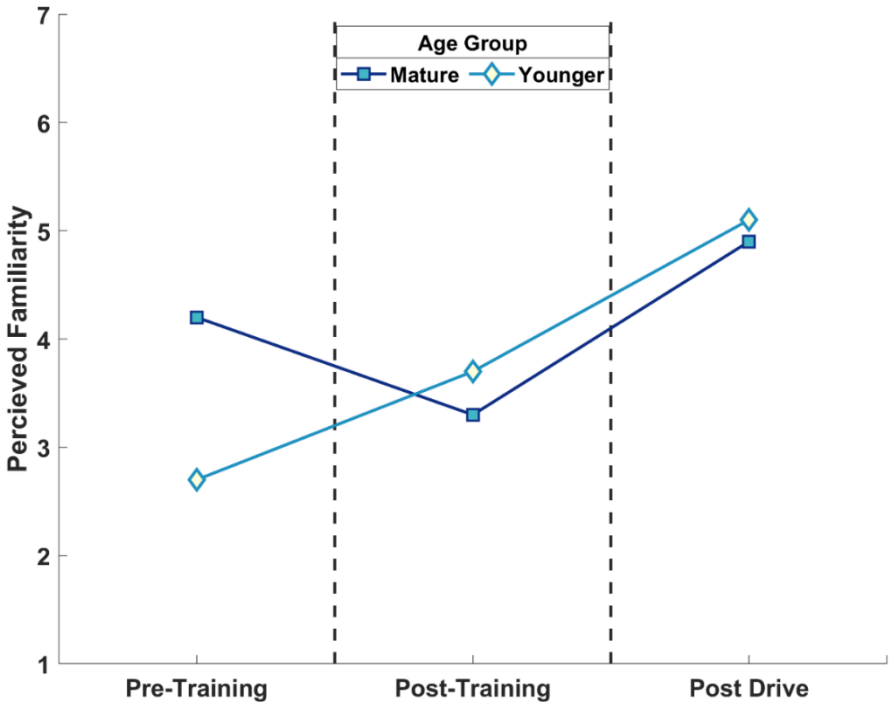


Figure 12. Changes in participants' perceived familiarity with vehicle automation with experience.

I trust vehicle automation. Participant's general agreement with the statement, "I trust vehicle automation" changed over time [$F(2,72)=9.55$, $p= 0.0002$, $\eta_p^2 =0.210$]. There was no difference in the pre-training and post-training responses ($M_{preT}=4.1$, $SD_{preT}=1.34$; $M_{postT}=4.15$, $SD_{postT}=1.33$), however, after driving the vehicle, the mean response increased to 4.75 ($M_{postDrive}=4.75$, $SD_{postDrive}=1.15$)

Perception of Training

No significant differences were found between the age groups or training groups regarding the perception of the training protocols they experienced. Results from the regression models can be found in Appendix E. Attitudes toward Training Regression. General trends in participant perception of training are shown in Table 12.

Table 12. Perception of training response by age group and training type

	Age Group	Training	Mean	SD	Min	Max
Objectives clearly defined	Mature	Conventional	6.4	0.70	5	7
		Multimedia	6.1	0.74	5	7
	Younger	Conventional	6.0	0.67	5	7
		Multimedia	6.2	0.79	5	7
Participation and interaction were encouraged	Mature	Conventional	6.4	0.52	6	7
		Multimedia	6.3	0.68	5	7
	Younger	Conventional	5.8	1.03	4	7
		Multimedia	6.2	1.03	5	7
Topics covered were relevant to me	Mature	Conventional	6.1	0.88	4	7
		Multimedia	5.7	1.06	4	7
	Younger	Conventional	5.3	1.06	3	7
		Multimedia	5.8	0.79	5	7
Content was well organized and easy to follow	Mature	Conventional	5.7	1.16	3	7
		Multimedia	5.9	0.74	5	7
	Younger	Conventional	6.1	0.99	4	7
		Multimedia	6.0	1.05	4	7
The time allotted for training was sufficient	Mature	Conventional	6.0	1.16	4	7
		Multimedia	5.7	1.16	3	7
	Younger	Conventional	6.2	1.03	4	7
		Multimedia	5.8	1.48	3	7
The training experience was useful in operating the vehicle automation.	Mature	Conventional	6.3	0.68	5	7
		Multimedia	6.1	0.60	5	7
	Younger	Conventional	6.2	0.79	5	7
		Multimedia	6.1	1.37	3	7
Do you feel the training adequately prepared you for operating the vehicle?	Mature	Conventional	5.7	1.25	3	7
		Multimedia	5.7	0.82	4	7
	Younger	Conventional	5.7	0.68	5	7
		Multimedia	5.0	1.25	3	6

Despite the favorable responses to the training sessions, no participants found the training alone to be helpful (Table 13).

Table 13. Participant response frequency to the question, "Which do you feel was more useful to your understanding of the automated vehicle system?"

		Training Module	Experience with Driving	Both Equally Helpful	Both Equally Unhelpful
Age Group	**Mature**	0	8	11	1
	Younger	0	14	6	0
	Age Group Total	0	22	17	1
		Training Module	**Experience with Driving**	**Both Equally Helpful**	**Both Equally Unhelpful**
Training	**Conventional**	0	12	7	1
	Multimedia	0	10	10	0
	Training Total	0	22	17	1

Discussion

In this study we examined whether mode of training protocol delivery influenced driver knowledge of vehicle automation, behavior during system use, and attitudes toward driving automation. The results of this study demonstrate that the mode of training protocol delivery elicits limited differences in knowledge scores and no difference in driver behaviors or attitudes. Behaviors and attitudes were influenced by time and experience with the driving automation system while knowledge of the vehicle systems remained unchanged.

These findings highlight some of the deficiencies of the content in owner's manuals. The content provided in owner's manuals is not sufficient to teach drivers about many system limitations. To increase safety, drivers need to be better educated about the capabilities and limitations of driving automation; brief experience with these systems after training does not sufficiently alter misconceptions about the boundaries of the systems' operational design domain. Drivers may become more aware of system limitations with prolonged exposure; however, previous studies have shown that safety-critical misunderstandings of system limitations persist over time (Kyriakidis et al., 2019; Larsson, 2012; Llaneras, 2006).

Operator behavior during system activation indicates an increased willingness to disengage from the task of monitoring the roadway during periods of automated driving. Our findings are

consistent with previous research indicating that drivers are more prone to becoming disengaged during automated driving conditions, which has been found in other studies to potentially lead to reduced performance when driver takeover is required (Banks, Eriksson, O 'donoghue, & Stanton, 2017; Merat, Jamson, Lai, & Carsten, 2012; Stanton, Young, & McCaulder, 1997). While increased mean off road glance durations for younger drivers while automated systems are active is concerning, these mean glance durations are still under the 2 second rule (National Highway Traffic Safety Administration, 2012). It is critical for drivers' trust to be calibrated according to the capabilities of the technology to avoid misuse of automation (Lee & See, 2004). This requires the development and assessment of training protocols that aim to educate drivers about operator-based errors in addition to machine-centered failures will lead to a training program that is holistic and encompasses the strengths and occasional deficiencies of both human and machine.

There are several limitations to this study. On a test track, participants may drive differently as compared to driving on a live roadway, and having a researcher in the vehicle may influence the driving behavior of participants. As with all human subjects research, the sample consisted of volunteer drivers which introduces self-selection bias. It is possible that there were some order effects associated with the Smart Road design as the trials were not counterbalanced. Future studies could improve upon this study design by changing the order in which participants experienced the driving automation and studying driver response and trust in association to system malfunctions over time.

In conclusion, the results of this study indicate that the general information provided in current training materials for driving automation systems may not be sufficient to educate operators about their role in completing the driving task. Participants reported increased familiarity with vehicle automation after driving the vehicle, however there were no significant differences in

their knowledge or driving performance at other points in the study. Our results suggest that understanding when and how drivers use the driving automation systems in their personal vehicles will provide insights into what behaviors should be targeted by future training efforts.

Chapter 3. A Naturalistic Evaluation of Driver Behavior Using Driving Automation Systems

The findings from the previous study indicated that the type of training yielded no differences in knowledge, behavior, and attitudes. However, driver experience with the driving automation system increased their perceived familiarity which may lead to complacency and inattention. This suggests that drivers may be more motivated to perform high-risk secondary tasks while using driving automation systems if they feel that the driving automation systems are capable of performing the primary task of driving sufficiently. This inaccurate belief could impede upon the driver's ability to successfully complete the OEDR sub-task.

Therefore, to understand if there is a difference in behavior when drivers are using driving automation systems compared to when the systems are available a high level analysis of their behavior was performed. This assessment was expected to shed light on when, where, and how drivers use their driving automation systems. The primary objective of this research was to identify if driver monitoring of the environment deviated from a pre-determined safety standard when driving automation features were being used and if the use of vehicle automation was a significant contributor to this behavior.

Research Objectives

The primary research objective of this study is to understand how drivers interact with the automated system in their own vehicle on real roadway environments.

Research Questions

Objective 1 – Quantify driver exposure to driving automation systems and determine the conditions under which drivers are more likely to choose to activate driving automation systems.

RQ 1. What percentage of driving exposure is assisted by level 2 driving automation systems? What influence do driver and vehicle characteristics have on system use?

RQ 2. Under what conditions are drivers more likely to activate level 2 driving automation systems?

Objective 2 – Assess differences in driver glance behavior while using driving automation systems.

RQ 3. Is driver eye glance behavior away from the forward roadway different during assisted driving compared to unassisted driving?

RQ 4. Is driver monitoring of the instrument panel different during assisted driving compared to unassisted driving?

Objective 3 – Assess differences in secondary task engagement while using driving automation systems.

RQ 5. Is there a difference in the likelihood of secondary task engagement when level 2 driving automation systems are active compared to when they are inactive?

RQ 6. Is there a difference in the likelihood of [high-risk] secondary task engagement when driving automation systems are active compared to when they are inactive?

Methods

Virginia Connected Corridors Naturalistic Driving Study

The data from the Virginia Connected Corridors (VCC 50) Naturalistic Driving Study (NDS) database was mined for this analysis. The VCC 50 NDS recruited 50 participants from Northern Virginia for this research effort. Participants were compensated $3,850 for full participation through the twelve-month enrollment period.

After affirming their consent using an informed consent document approved by the

Virginia Tech IRB, participants were asked to complete a set of driver assessment questionnaires. The assessments included cognitive, physiological, and psychosocial tests that were administered via electronic computer program. Some tests were completed onsite during installation and while others were completed using an online questionnaire administration system from the participant's personal computer.

Recruitment Criteria. Participants were recruited through the VTTI database of potential participants as well as through flyers, brochures, newspaper advertisements, and direct recruiting methods via purchase records. Participants in this study were required to be at least 18 years old with a valid driver's license and at least two years of driving experience. They must have owned, co-owned, or leased the vehicle and been the primary driver of the vehicle (75% of the time, minimum). The vehicle to be instrumented must have had at least the minimum amount of liability insurance coverage required by the state or the district in which it is registered and been equipped with adaptive cruise control. Additionally, participants were required to live or work in the Northern Virginia or DC area and have a reasonable expectation of driving on I-495, I-66, Rt. 123, and Rt. 50 at least two to three times per week. In the screening interview, participants were asked how many miles on average they were driving on the required roadways. Preference was given to those who drove more trips and more miles.

Apparatus. Participant vehicles were instrumented with a data acquisition system (DAS) which collected data using a number of sensors and video cameras. The DAS collected data continuously from the time the vehicle was powered on until the time that the vehicle was powered off. The DAS featured multiple sensors including GPS, radar, lane tracker, accelerometers, as well as six video cameras (Figure 13) mounted unobtrusively to facilitate observation of naturalistic driving behavior. The camera views used in the analyses included a view of the forward roadway,

the driver's face, the vehicle foot well, rear of the vehicle, and the instrument panel. Frame numbers were used to synchronize video and vehicle data.

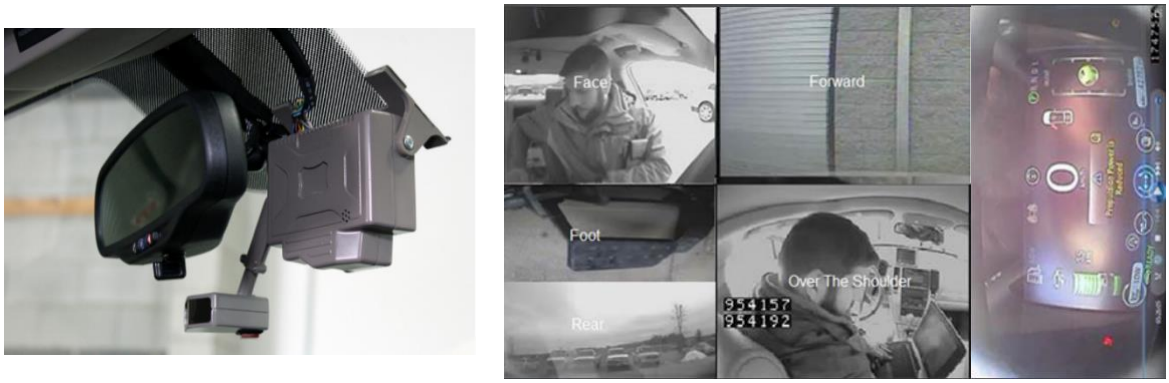


Figure 13. The DAS Head Unit (left) was mounted behind the vehicle's rearview mirror. The six camera views captured during the VCC 50 study are shown (right).

Machine Vision Algorithm for System Status Identification. The status for Adaptive Cruise Control and Lane Keeping Assist were identified at three levels using a post-processing machine vision algorithm and the camera view of the instrument panel, shown in Figure 13. Due to errors in time mapping between the two data acquisition systems used in this study, it was not possible to identify system status for all trips. Additional details about algorithm limitations can be found in Appendix I. A Naturalistic Evaluation of Driver Behavior Using Driving Automation Systems - Algorithm Limitations. Please note that while 32 of the 50 participants who volunteered for the VCC 50 study had vehicles which were equipped with both adaptive cruise control and lane keeping assistance systems, only 25 of those vehicles had icons of quality for the machine vision algorithm application and were included in this analysis (see Appendix I. A Naturalistic Evaluation of Driver Behavior Using Driving Automation Systems - Algorithm Limitations for additional details).

Data Sampling

Data about system status was available for approximately 21,808 trips across the 25 participant vehicles. Kinematic data as well system status were available for the full length of the

trip file. Data were sampled strategically to best answer the research question presented. Sampling strategies are described below.

Sample 1 – Trip Summary Sample. To understand the percentage of overall travel time and trip and driver specific factors associated with system use, a broad sampling strategy was employed for research question 1. All trips for subject vehicles were included in this sample. An instance of level 2 system activation must have been a minimum of five seconds in duration and meet the speed based criteria for activation of 40 miles per hour.

Sample 2 – System Activation – Case Control. Research question two focuses on determining under which conditions drivers were more likely to activate their driving automation systems. Therefore, the total number of system activations were identified to determine the number of cases present in the dataset; these cases were proportionally sampled and stratified by driver to provide a case-control dataset for comparison. The criteria for the selection of cases and controls are described below:

Identification of cases. Several criteria needed to be met for instances of system activation (cases) to be included in the sample.

1) Both driving automation systems (ACC and LKA) needed to be active for at least five seconds
2) The speed of the subject vehicle must have been at least 40 miles-per-hour
3) The positional dilution of precision (PDOP) must have been 8 or less, which indicates that these measurements could be used for calculations, such as speed (Person, 2008).

This technique resulted in over 44,000 samples to choose from. Given the sensitivity to certain statistical methods to large sample sizes, 6,215 of these samples were used. Following the

general rule of 10 cases per every independent variable in the model this is an appropriate selection (Peduzzi, Concato, Feinstein, & Halford, 1993). These samples were proportionally stratified by driver by number of system activations and selected randomly.

Identification of controls. Controls were identified by finding points in the data stream where systems were inactive for a minimum of five seconds and met the aforementioned PDOP and speed criteria. This resulted in over 128,000 controls that could be sampled. Ultimately, over 4,000 samples were proportionally stratified by driver and sampled randomly.

Table 14. System Activation – Case Control Sample Description

	Cases (Active)	**Controls (Inactive but available)**
Number of Samples	44,489	128,701
Number of Vehicles	21	21
Number of Trips	6,043	6,239
Samples Used	4,197	4,168

Sample 3 – Eye Glance and Secondary Task Samples. This sample of the data was used to determine if driver eye glance behavior and secondary task engagement is different when driver assistance systems were active compared to when they were available but not active. For each participant, eight epochs where drivers were using their vehicle's level 2 (ACC+LKA) systems were identified. Each of these epochs were 10 seconds in duration and coded using a battery of variables by trained data reductionists (for additional information see Researcher Dictionary for Safety Critical Event Video Reduction Data Version 4.2, Virginia Tech Transportation Institute (2009)). For each selected case of system activation, instances of where the systems were inactive but available were also identified and matched to the active case. Matching was based on time of day (6 a.m.–8:59 a.m., 9 a.m.–3:59 p.m., 4 p.m.–6:59 p.m., 7 p.m.–10:59 p.m., 11 p.m.–5:59 a.m), day of week (weekday vs. weekend), and vehicle speed (± 5 mph, with a minimum vehicle speed of 20 mph). Matched control samples received the same coding as

the case samples. The observations from this protocol are listed in Table 15. Appendix J. Defining on Road Glance Locations contains descriptions of on road and off road glance locations.

Table 15. Summary Eye Glance and Secondary Task Samples

Sample Group	N Samples	N Drivers	Average per Driver
Both Active	151	19	7.95
Both Available	148	19	7.79

Independent Factors

Independent factors in this analysis include driver specific factors, vehicle specific factors, trip level information, temporal information, and exposure based information. Table 16 provides a description of all independent factors that were utilized in this study.

Table 16. Overview of Independent Factors

Group	Variable Name	Type	Levels	Description
Driver	Length of Vehicle Ownership (LVO)	Categorical	2	At the time of study, enrollment participants indicated the length of vehicle ownership. Participants were classified into one of two groups based on their response. • Less than one year • One year or longer
Vehicle	Lateral Control (LatCtrl)	Categorical	2	• Proactive Systems: Attempt to keep you centered in the lane • Reactive Systems: React when possible lane departure is detected.
Trip	Trip Duration Cat	Categorical	5	• 1: $t < 15$ minutes • 2: $15 \leq t < 30$ minutes • 3: $30 \leq t < 45$ minutes • 4: $45 \leq t < 60$ minutes • 5: $t \geq 60$ minutes and beyond
Trip	L2 System Status	Categorical	2	• L2 Active: System is actively maintaining lateral and longitudinal control of the vehicle • L2 Inactive: Driver is responsible for maintaining the lateral and longitudinal control of the vehicle

Trip	Speed Bin	Categorical	4	The average speed across a one-second interval of observation were categorized into the appropriate bin. • 1: 40 mph ≤ v < 45 mph • 2: 45 mph ≤ v < 55 mph • 3: 55 mph ≤ v < 60 mph • 4: 60 mph ≤ v
Temporal	Time of Day	Categorical	6	Start hour of the trip recorded in local time was categorized as: • 11 PM - 2:59 AM: Late Night/Early Morning • 3 AM - 6:59 AM: Pre-Morning Peak • 7 AM - 10:59 AM: Morning Peak • 11 AM - 2:59 PM: Mid-Day • 3 PM - 6:59 PM: PM Peak • 7 PM - 10:59 PM: Evening/Night
Temporal	Day of Week	Categorical	2	The day of the week that the trip occurred as recorded by the DAS: • Weekday: Monday – Friday • Weekend: Saturday – Sunday
Roadway	Lane Category (LC)	Categorical	3	• 1 = One lane • 2 = Two or three lanes • 3= Four or more lanes
Roadway	Controlled Access	Categorical	2	• Y = the link is controlled access • N = the link is not controlled access

Driver Characteristics. The following driver characteristics were considered as independent factors in this study.

Length of Vehicle Ownership. To understand participant familiarity with advanced vehicle systems prior to study enrollment, participants were asked how long they owned the vehicle that they were having instrumented in the study. Of the 33 operators of vehicles with L2 capabilities, 20 participants reported having their vehicles for less than one year, while 13 reported having their vehicle for more than one year.

Vehicle Characteristics. Vehicle specific characteristics were analyzed to better understand how system design and vehicle capabilities influence driver behavior and system use.

Lateral Control Capabilities. Level 2 Partial Driving Automation specifies that lateral and longitudinal control can be controlled by the vehicle. However, driver perception of system capabilities can cause the driver to allocate components of the DDT to the driving automation that it is not designed to perform for a sustained basis. Therefore, to determine if behavior varies depending on the fidelity of lane keeping assistance technology on the vehicle two categories were defined; reactive and proactive. Of the 25 vehicles included in this analysis, 9 vehicles had reactive lateral control systems while 12 vehicles had proactive systems.

Trip Characteristics. A trip file for the VCC50 dataset began when the vehicle's ignition was turned on (allowing approximately 30 seconds for system start-up, (Hankey, Perez, & McClafferty, 2016)) and ended when the ignition was turned off. Exceptions to this occurred for longer trips (which were spliced into approximately two-hour segments) and cases of low battery voltage from the participant vehicle.

Trip Duration Categorical. Trip duration was the time duration between maximum timestamp and minimum timestamp. The duration of the trip was converted into a categorical factor (listed below) for use in research question 2.

- 1: less than 15 minutes
- 2: 15 - < 30 minutes
- 3: 30 - < 45 minutes
- 4: 45 - < 60 minutes
- 5: 60 minutes and beyond

System Status. System Status refers to the status of the driving automation system at the analysis epoch. This binary categorical factor was either System Active which indicates the driving automation system was actively maintaining lateral and longitudinal control of the vehicle or System Inactive [but available]. This means that driver was responsible for maintaining the lateral and longitudinal control of the vehicle.

Speed Bin. The binning method in Table 17 was based on the Roadway design classification flow chart for suburban and urban roadways (Fitzpatrick, Carlson, Brewer, Wooldridge, & Miaou, 2003). The anticipated operating speed/adjusted posted speed limit served as a surrogate for roadway design class and service type. These speed breakdowns took into account that the maximum posted speed limit in Northern Virginia was 60 miles per hour.

Table 17. Speed Bins (Fitzpatrick et al., 2003)

Speed Bin	Speed Ranges
1	40 mph $\leq v <$ 45 mph
2	45 mph $\leq v <$ 55 mph
3	55 mph $\leq v <$ 60 mph
4	60 mph $\leq v$

Context. Driver assistance systems such as ACC and LKAS were designed to be used in certain situations based on their operational design domain (ODD) (SAE International, 2018). However, users may choose to disregard the intended use of a system for a variety of reasons such as prior experience, system design, and misunderstandings (Godfrey et al., 1983; Riley, 2014). By evaluating the conditions under which driving automation was used (and disused), driver understanding of ODD boundaries can be inferred. Levels of the independent variables are described below:

Time of Day. The local start and end times for the trips were recorded. This allowed for time of day conditions to be calculated. Time of day groupings were determined based on the trip start hour, further categorized by traffic-volume projections for urban cars denoted by the Federal Highway Administration (Federal Highway Administration, 2014) as shown in Table 18 and Figure 14.

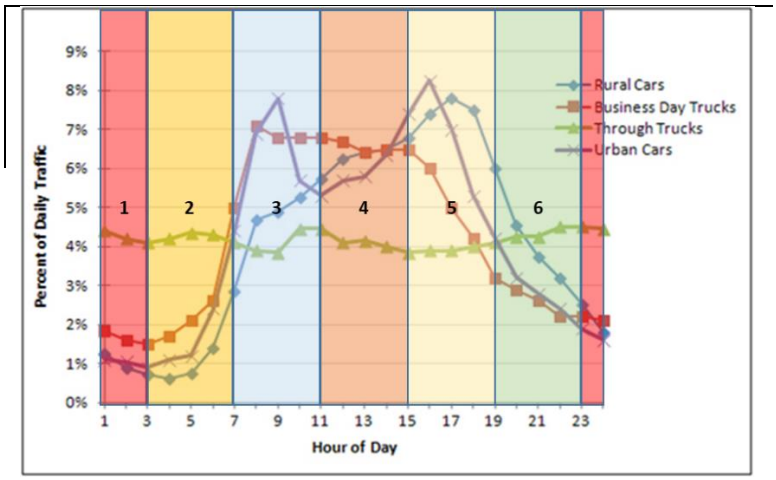


Figure 14. Visualization of 24-hour day segmented into bins.

Table 18. Trip Distribution by Time of Day

Time Of Day		ACC+LKA	
		Frequency	**Percent**
1	11 p.m.–2:59 a.m.: Late Night/Early Morning	1,438	6.59%
2	3 a.m.–6:59 a.m.: Pre-Morning Peak	1,228	5.63%
3	7 a.m.–10:59 a.m.: Morning Peak	4,601	21.10%
4	11 a.m.–2:59 p.m.: Mid-Day	5,948	27.27%
5	3 p.m.–6:59 p.m.: p.m. Peak	6,167	28.28%
6	7 p.m.–10:59 p.m.: Evening/Night	2,426	11.12%
	Total:	**21,808**	**100%**

Day of Week. The day of week that the trip was taken was recorded by the DAS. This allowed for weekday and weekend trips to be considered as a categorical factor where "Weekday" consisted of trips beginning Monday through Friday and "Weekend" consists of trips beginning on Saturday or Sunday.

Roadway Characteristics. Roadway features were identified using the Navteq Relational Database. Specific roadway features of interest included number of lanes (lane category) and access type for road segments.

Lane Category. The number of lanes for the specific road segment in the direction of travel were identified in the Navteq database by lane category (LC) a categorical factor.

Table 19. Lane Category Description

Lane Category	Number of Lanes
1	One lane
2	Two or three lanes
3	Four or more lanes

Controlled Access. This factor identified roadways with limited entrances and exits that allow uninterrupted flow of high-speed traffic. This factor was binary where "Y" indicated, "Yes" the road segment was controlled access. "N" indicates, "No, the road segment was not controlled access."

Dependent Measures

The dependent measures to answer the research questions are described below. The measures major categories of the dependent factors are system use, eye glance behavior, and high-risk secondary task engagement.

Exposure. Driving exposure was measured as a time-based measure as it was measured directly from the DAS.

Overall Driving Exposure. Participant driving exposure was the total amount of time spent operating the vehicle (either assisted or unassisted) while enrolled in the study. This was the sum of all trips made by a driver while enrolled in the study.

Driver Assistance System Exposure. The purpose of the system use measure was to understand how much time drivers spend using advanced vehicle systems when they were in their own vehicles (under uncontrolled conditions). These analyses also shed light on under what conditions drivers choose to activate these systems and how closely they aligned with the conditions specified by the vehicle manufacturer and SAE guidelines. The dependent measures for system use are described below:

Percentage of time L2 Systems Active when Available. The cumulative measure of simultaneous exposure to both Adaptive Cruise Control and Lane Keep Assistance Systems served as a continuous dependent factor in characterizing the use of level 2 systems during study enrollment. This consisted of cases where both lateral and longitudinal control had been relinquished by the driver. The availability of the L2 systems was determined by the speed based criteria for system activation across all vehicle types; most commonly, 40 mph was required for lateral control to be relinquished. Given the variable nature of the vehicles in the study, only L2 exposure was considered and not any one system in isolation.

Level 2 System Status. System status served as a dichotomous dependent measure to aid in understanding under what conditions drivers were most likely to activate the level 2 Systems. There was a corresponding number of driver stratified random sampled baselines for each case condition (detailed on page 64).

Eye Glance Behavior. Monitoring the environment and determining the field of safe travel remained the responsibility of the human operator when using level 2 driving automation. This is a fundamental component to the driving task and excessively long off road glances increase the odds of crash involvement (Dingus & Klauer, 2008).

Off Road Glance Measures. On road glance locations consisted of glances to the following locations in most analyses: Forward Windshield, Instrument Cluster, Left Mirror, Rearview Mirror, and Right Mirror. A detailed description of the on and off road glance locations used in this study can be found in Appendix J. Defining on Road Glance Locations. Measures are described in Table 20.

Table 20. Naturalistic Driving Study Eye Glance Measures

Glance Measure	Acronym	Description
Total Eyes off Road Time	TEORT	The summation of all glance durations to all AOIs other than the road scene ahead during a sample interval in seconds (SAE International, 2017).
Mean Off Road Glance Duration	MGOR	The average duration of all glances away from the road scene during the 10-second sample interval.
Single Longest off Road Glance	SLG	The duration of the single longest glance away from the road scene during the sample interval.
Number of off Road Glances	NORG	The number of glances away from the road scene during the 10-second sample interval.

Instrument Panel Glance Measures. One of the driver's responsibilities was to monitor the driving automation system. Key visual stimuli that were not contained in the forward roadway pertaining to automated system performance are found on the instrument panel. Therefore, glances to the instrument panel were assessed separately from the off road measures. Glance measures to the instrument panel are described in Table 21.

Table 21. Eye Glance Measures to Instrument Panel

Glance Measure	Description
Total glance duration to the instrument panel	The sum of the duration of all glances to the instrument panel during the sample interval.
Single longest glance to instrument panel	The instrument panel was the duration of the single longest glance to the instrument panel during the sample interval.
Mean glance duration to instrument panel	The instrument panel was the average duration of all glances to the instrument panel during the 10-second sample interval.
Number of glances to the instrument panel	The number of glances to the instrument panel during the 10-second sample interval.

Secondary Task Engagement. Epochs of secondary task engagement are identified within the data sampled using the method described on page 65. Overall and high-risk secondary task engagement were considered and are described below.

Overall Secondary Task Engagement. Overall secondary task engagement only examined Secondary Task 1 since, if at least one secondary task is being performed it will be captured there.

High Risk Secondary Task Engagement. Guo et al. (2017) identified the odds of crash involvement for secondary-task engagement for four different driver age groups; Teen, Young Adult, Middle, and Senior. Drivers in this dataset were consistent with those in the Young Adult, Middle, and Senior age groups, the observable distractions with significant odds ratios across these three age groups was considered high risk for this analysis.

- **Cell-phone use (visual-manual tasks)** was found to increase crash risk for drivers. It was comprised of the following observed behaviors:
    - Cell texting: Cell-phone texting
    - Hand-held dialing: Cell-phone dialing hand-held, including using quick keys
    - Cell reaching: Cell-phone locating/reaching/answering
- **Looking outside of the vehicle**: Looking at an object external to the vehicle/animal/ pedestrian/previous crash or incident
- **Reaching for in-vehicle object (not cell phone)**: Reaching for cigar or cigarette/food-related or drink-related item/personal body-related item/other object, interaction with moving object

Analyses

A variety of analyses (descriptive and inferential statistics) were employed to assess the aforementioned research questions, which are restated below. For all analyses, statistical significance was evaluated at $\alpha = 0.05$.

To assess which factors influenced the proportion of time that drivers used their driving automation systems, a mixed effects general linear model with a driver-specific random driver

effect was used The numerator was the cumulative system active time where the system was active for 5 seconds or longer for a given trip. This was divided by the total trip duration. The conditions under which drivers were most likely to activate their automated assistance systems was assessed using a mixed effects logistic regression with a driver-specific random effect to estimate the odds ratios of system activation associated for particular driver, trip, and environmental factors.

In order to determine if driver eye glance behavior to both the driving environment and to the instrument panel was significantly different while using driving automation systems compared to when driving automation systems were not active but available, a mixed effects general linear model with a driver-specific random driver effect was used.

A mixed effects logistic regression model was also used to obtain odds ratios for the likelihood of secondary task engagement with ACC+LKA active compared to when it was available but inactive for each level of secondary task. In the cases where the convergence criteria were not met a conventional logistic regression model was used.

Table 22 re-iterates the research questions of interest for this study and introduces the dependent measures which were used to answer these questions as well as the proposed statistical analyses.

Table 22. Research Overview for Study 2

Objective	Dataset	Research Question	Dependent Measure(s)	Independent Factor(s)	Statistical Methods
Exposure	1	Q1A. What percentage of driving exposure was assisted by ACC+LKA?	Time ACC+LKA Active / Time ACC+LKA Available		Summary Statistics
Exposure	1	Q1B. What was the distribution of ACC+LKA exposure?	Time ACC+LKA Active / Time ACC+LKA Available	Time of day Day of Week Lateral Control Length of Vehicle Ownership	GLM with driver random factor
Exposure	2	Q2. Under what conditions were drivers most likely to activate ACC+LKA systems?	ACC+LKA Status (Active vs. Available)	Trip Duration Categorical Speed Bin Time of Day Day of Week Controlled Access Lane Category	Mixed Effects Logistic Regression
Eye Glance Behavior	3	Q3. What was the frequency and duration of off road glances when ACC+LKA were active compared to when they were inactive but available?	TEORT MGOR SLG Number of off road glances	ACC+LKA Status (Active/Available)	GLM with driver random factor
Eye Glance Behavior	3	Q4. What is the frequency and duration of glances to the instrument panel when ACC+LKA systems were active compared to when they were inactive but available?	TEORT MGOR SLG Number of off road glances	ACC+LKA Status (Active/Available)	GLM with driver random factor
Secondary Task	3	Q4. Were drivers more likely to engage in high-risk secondary tasks when ACC+LKA systems were active compared to when they were inactive but available?	High-Risk Task Engagement (Yes/No)	ACC+LKA Status (Active/Available)	Mixed Effects Logistic Regression

Results Assisted Driving Exposure

When assessing how often drivers use their L2 systems, we found that drivers used these systems for roughly 8.6% of (SD = 16.6%). Day of week was found to significantly influence the percentage of trip duration that L2 systems were active [$F(1, 21781) = 4.26$, $p = 0.0389$]. Drivers used their L2 systems longer on weekdays (M=9.1%, SD=16.9%) than on weekends (M=7.4%, SD=15.7%).

Conditions of Activation

For drivers using both ACC+LKA the logistic regression indicated that drivers were less likely to activate these two systems together when the trip was under 15 minutes and more likely to activate the two systems when the trip was over 30 minutes in duration. Additionally, drivers were more likely to activate these two systems together at speeds greater than 45 mph and 10 times more likely at speeds greater than 60 mph (OR: 10.6, [CI: 8.9, 12.7]). Drivers were significantly less likely to activate ACC+LKA at speeds less than 30 mph (OR: 0.6, [CI: 0.56, 0.84]). Finally, drivers were more likely to activate ACC+LKA together on controlled access roadways than on uncontrolled access roadways and on roadways with greater than two lanes present (Table 23). Time of day did not appear to make a difference for these drivers using ACC+LKA, but drivers using both ACC and LKA did activate these systems more frequently on weekends than on weekdays (OR: 1.21, [CI: 1.04, 1.40]).

Table 23. Odds Ratio Estimates for ACC+LKA Conditions of Activation

Factor		Reference	OR	DF	95% CL		Sig
					LL	UL	
Dur_Cat	1: less than 15 minutes	2: 15–30 minutes	0.68	8,328	0.56	0.84	*
	3: 30–45 minutes	2: 15–30 minutes	1.31	8,328	1.12	1.53	*
	4: 45–60 minutes	2: 15–30 minutes	1.46	8,328	1.22	1.74	*
	5: 60 minutes and beyond	2: 15–30 minutes	1.37	8,328	1.19	1.58	*
TOD	11 p.m.–2:59 a.m.: Late Night/Early Morning	11 a.m.–2:59 p.m.: Mid-Day	1.07	8,328	0.76	1.52	
	3 a.m.–6:59 a.m.: Pre-Morning Peak	11 a.m.–2:59 p.m.: Mid-Day	0.78	8,328	0.60	1.02	
	7 a.m.–10:59 a.m.: Morning Peak	11 a.m.–2:59 p.m.: Mid-Day	1.10	8,328	0.92	1.31	
	3 p.m.–6:59 p.m.: p.m. Peak	11 a.m.–2:59 p.m.: Mid-Day	1.01	8,328	0.85	1.22	
	7 p.m.–10:59 p.m.: Evening/Night	11 a.m.–2:59 p.m.: Mid-Day	1.17	8,328	0.94	1.47	
DOW	Weekend	Weekday	1.21	8,328	1.04	1.40	*
SpeedBin	4: 45 mph ≤ v ≤ 55 mph	3: 40 mph ≤ v < 45 mph	2.39	8,328	2.02	2.83	*
	5: 55 mph ≤ v < 60 mph	3: 40 mph ≤ v < 45 mph	5.91	8,328	4.84	7.20	*
	6: 60 mph ≤ v	3: 40 mph ≤ v < 45 mph	10.63	8,328	8.89	12.70	*
Lane Category	2: 2–3	1: 1 lane	1.85	8,328	1.60	2.12	*
	3: 4 +	1: 1 lane	1.89	8,328	1.58	2.26	*
Controlled_Access	Y	N	1.24	8,328	1.08	1.42	*
LVO	1 year or longer	Less than 1 year	0.88	8,328	0.56	1.37	
LatCtrl	PROACTIVE	REACTIVE	1.12	8,328	0.73	1.72	

Frequency and Duration of Off Road Glances

ACC+LKA activation epochs from 19 drivers were used for this analysis. These events consisted of 203 epochs where both ACC+LKA were active and 200 samples where both systems were available but inactive. The results from the mixed-effects general linear model indicated that ACC+LKA status does influence to driver's total eyes off road time [F (1, 279) = 8.83, p = 0.0032]. Driver's total eyes off road time was greater when ACC+LKA systems were active (M = 1.54, SD = 2.00) compared to when they were available but inactive (M = 0.97, SD = 1.24). There was no significant difference in the average off road glance duration between when systems were active and when they were available but inactive [F (1, 279) = 1.74, p = 0.1744].

System status was found to significantly influence a driver's single longest off road glance [F (1, 279) = 4.94, p = 0.0271]. The single longest glance away from the forward roadway was significantly longer when ACC+LKA systems were active (M = 0.79, SD = 1.04) compared to when the systems were available but inactive (M = 0.57, SD = 0.59). Furthermore, ACC+LKA status significantly influenced the number of glances drivers took away from the forward roadway [F (1, 279) = 11.99, p = 0.0006]. When systems were active, drivers took more glances away from the forward roadway (M = 1.83, SD = 1.93) compared to when the systems were available but not active (M = 1.32, SD = 1.40).

Table 24. Off Road Glance Measures ACC+LKA Summary Stats

Measure	System Status	N	Mean	SD	SE	Min	Max	Sig
TEORT	Active	151	1.54	2.00	0.16	0.00	8.88	Y
	Available	148	0.97	1.24	0.10	0.00	6.41	
MGOR	Active	151	0.54	0.60	0.05	0.00	4.44	N
	Available	148	0.46	0.44	0.04	0.00	1.70	
SLG	Active	151	0.79	1.04	0.08	0.00	8.28	Y
	Available	148	0.57	0.59	0.05	0.00	3.27	
NORG	Active	151	1.83	1.93	0.16	0.00	11.00	Y
	Available	148	1.32	1.40	0.12	0.00	6.00	

Frequency and Duration of Glances to the Instrument Panel The results of the mixed-effects general linear models of driver glances to the instrument panel are summarized in Table 25. The results indicated that the driving automation system status did not contribute significantly to drivers' total glance duration to the instrument panel [F(1, 279) = 3.31, p = 0.0699]. Furthermore, there was no significant influence for single longest glance duration to the instrument panel [F(1, 279) = 2.51, p = 0.1141] or mean glance duration to the instrument panel [F(1, 279) = 1.83, p = 0.1775]. However the number of glances to the instrument panel was significantly influenced by automation status [F(1, 279) = 5.01, p = 0.0259]. Drivers looked at the instrument panel more frequently when automation was active compared to when it was available – which one would expect. However, the average number of glances were still quite small and did not appear to indicate practical significance.

Table 25. Glances to the instrument panel

Measure	System Status	N	Mean	SD	SE	Min	Max	Sig
Total glance duration to the instrument panel	Active	151	0.27	0.66	0.05	0.00	4.40	N
	Available	148	0.15	0.4	0.03	0.00	2.74	
Mean glance duration to instrument panel	Active	151	0.16	0.34	0.03	0.00	1.67	N
	Available	148	0.12	0.27	0.02	0.00	1.20	
Single longest glance to instrument panel	Active	151	0.19	0.4	0.03	0.00	1.87	N
	Available	148	0.12	0.29	0.02	0.00	1.27	
Number of glances to the instrument panel	Active	151	0.39	0.79	0.06	0.00	4.00	Y
	Available	148	0.24	0.61	0.05	0.00	4.00	

Secondary Task Engagement The results from the logistic regression (Table 26) indicated that drivers were more likely to use their cellphone when using both ACC and LKA systems (OR: 2.59, [CI: 1.02, 6.60]). Drivers were more likely to perform visual-manual cellphone tasks when the systems were active compared to when they were available but inactive (OR: 2.96, [CI: 1.01, 6.646]). Specifically, drivers were five times as likely to be observed browsing on their cellphones while using their ACC+LKA systems (OR: 5.21, [CI: 1.10, 24.6]).

Table 26. Prevalence and Odds Ratio Estimates for Secondary Task Engagement while ACC+LKA were Active compared to when they were Inactive but Available

Task	Prevalence		Odds Ratio (ref: Both Available)	DF	95% Confidence Interval		Sig.
	ACC+LKA Active	ACC+LKA Available			LL	UL	
Number of observations	151	148					
Any Task	58.9%	52.0%	1.334	279	0.837	2.13	
All Phone	11.3%	4.7%	2.594	279	1.02	6.599	*
Cellphone (visual-manual)	9.3%	3.4%	2.958	279	1.01	8.65	*
Talking (cell phone)	2.0%	1.4%	1.514	279	0.24	9.547	
Texting [a]	1.3%	0.0%	> 999.9	297	< 0.001	> 999.9	
Dialing	0.0%	0.0%					
Browsing	6.6%	1.4%	5.213	279	1.104	24.62	*
Reaching (cell phone) [a]	1.3%	0.0%	> 999.9	297	< 0.001	> 999.9	
External distraction	4.0%	1.4%	3.021	279	0.596	15.32	
Reaching for object (non-cellphone)	3.3%	0.7%	5.05	279	0.577	44.18	
Operating in-vehicle device	25.2%	26.4%	0.942	279	0.559	1.59	

[a] Indicates conventional logistic regression was used.

Discussion

In this study we examined when and how drivers utilized the driving automation systems on their personal vehicles. The results from the assessment of the conditions in which drivers activated their driving automation systems indicated that drivers used these systems more frequently in appropriate roadway environments, such as when traveling above 45 mph, on controlled access roadways, and on roadways with multiple lanes of traffic. While the odds ratios showed activations more often under these conditions, these results did not indicate that drivers activated driving automation systems solely on controlled access roadways. For example, drivers were only 24% more likely to activate ACC+LKA on controlled access roadways than on uncontrolled access roadways. The odds ratios were much higher for activation of driving automation systems when traveling at higher speeds and on roads with multiple travel lanes.

Drivers tended to activate ACC+LKA systems more frequently in appropriate roadway environments, such as when traveling above 45 mph, on controlled access roadways, and on roadways with multiple lanes of traffic. The behavioral trends for conditions of use are encouraging because they indicate that drivers were generally activating and using driving automation systems in the roadway environments for which the systems were designed.

Several eye glance metrics in relation to the driving scene and to the instrument panel were evaluated with regard to the status of the driving automation system (active vs. inactive). Additionally, secondary task engagement when systems were active was compared to secondary task engagement when systems were available but inactive.

Drivers generally looked away from the forward roadway significantly longer when the systems were active versus when the systems were available but not active. However, there were very limited differences in the frequency of glances to the instrument panel when automation was

active (M=0.39, SD=0.79) compared to when it was available (M=0.24, SD=0.61). Driver engagement in high-risk secondary tasks such as cellphone browsing were noted to be higher for drivers using both ACC+LKA versus when the systems were available but not active.

The following limitations should be considered when interpreting the results of this study. This dataset is a sample of drivers who live or work in the Northern Virginia or DC area and may not be representative of all drivers. As with all human subjects research, the sample consisted of volunteer drivers which introduces self-selection bias. The participants in this study had their personal vehicles instrumented however due to aggregation of the survey instrument data it was impossible to know precisely how long they owned their vehicle prior to study enrollment, therefore it was impossible assess how driver behavior changes with exposure to the driving automation.

This study also uses a broad definition of driving automation systems. Level 2 driving automation is defined by SAE International J3016 as the use of ACC and Lane Centering technology. The condition of combined use of ACC plus lane keeping in this study can be generalized to L2 in some, but not all instances. Therefore it is important to note that of the 21 vehicles in this sample 12 vehicles were equipped with lane centering systems and 9 were equipped with lane keeping systems.

In the analysis of secondary task engagement, the prevalence of cell phone, talking/listening, hands-free may be underestimated due to the increased prevalence of Bluetooth technology and integrated speakerphones. New data reduction protocols have been developed to remedy this limitation but were not available at the time of this study. A video based machine vision algorithm was used to identify driving automation system status which could not be collected directly from the vehicle network, therefore the conditions of availability are our best

approximation based on speed and ACC/LKA system design. Future research efforts should attempt to use network data to ensure the most precise data available. Finally this was a relatively small sample of reduced samples in this dataset for comparison between assisted and unassisted driving. Future research would benefit from larger sample sizes of secondary tasks to assess if other driver behaviors beyond cellphone browsing are more prevalent in ACC+LKA driving situations.

Based on the groundwork laid by Parasuraman and Manzey (2010) we have observed an environment conducive to driving automation-related complacency. Current driving automation features require human monitoring of automation system components and the results of our study show that drivers of vehicles are inclined to engage in secondary tasks and take longer and more frequent glances away from the forward roadway. While drivers in the present study tended to use their driving automation systems in the appropriate environments; whether it be a function of system design or knowledge, their behavior while the driving automation systems were active indicated that they were demonstrating behaviors that indicated they were not be sufficiently monitoring the driving environment or the driving automation system. It is possible that performance effects, such as omission errors or delayed reactions, may occur as a result of drivers' substandard monitoring of the driving scene. Therefore, in order to develop and deliver effective training interventions and deliver feedback when it is needed most, we must understand how driver behavior changes as they gain experience with driving automation systems.

Chapter 4. Behavioral Adaptation with Driving Automation at Early Exposure

The use of vehicle automation may exacerbate pre-existing time-variant risk factors such as engagement in non-driving related tasks that could contribute to crash involvement. In ordinary driving, the status of these factors change constantly, often in terms of seconds, with their associated crash risk only increasing when they are present (Guo, 2019). When driving automation is being used, it is possible that these transient behaviors could become more frequent as drivers become more familiar with driving automation systems. Prior research from aviation and surface transportation has indicated that users have a tendency to reduce their monitoring of highly reliable automated systems and the environment (Llaneras et al., 2013; Mosier et al., 1998; Parasuraman et al., 2008).

Manser et al. (2013) discussed the temporal factors that may affect driver behavior after the introduction of a change in the road system. Changes in the road system could include the introduction of new in-vehicle equipment or behavioral shifts that occur after this introduction. Three points of driver exposure to the implemented change are mentioned and depicted in Figure 15: 1) the immediate phase, which occurs immediately after a driver experiences the change; 2) the short-term phase, occurring hours, days or weeks after the introduction of the change; and 3) the long-term phase, which transpires after months or years. The early exposure period for the purpose of this research is described as the collective immediate and short-term phase of exposure (henceforth referred to as “exposure”) to a change in the road system.

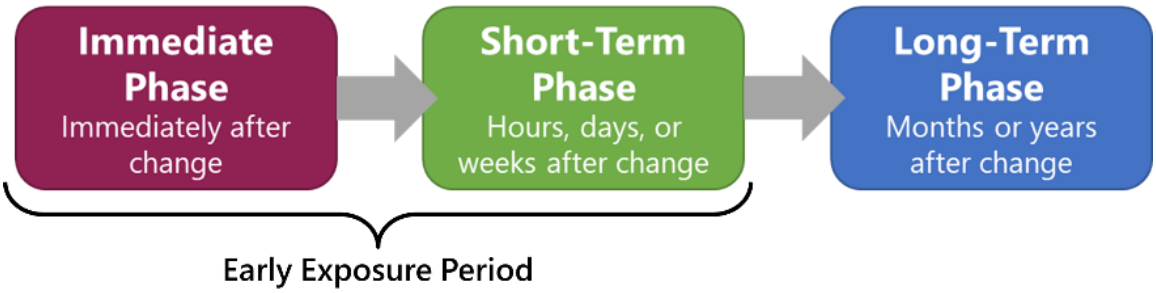


Figure 15. Depiction of the exposure period described by Manser et al. (2013). The combination of the Immediate Phase and Short-Term phase will be described as the Early Exposure period.

Research Objectives

The primary aim of this study is to identify changes in operator behavior as a function of exposure to the driving automation system to assist in targeted retraining and understand the approximate time at which interventions would be most beneficial. Two main objectives comprise the primary aim of this study.

1. Assess how driver performance changes with exposure to the level 2 system *compared to unassisted driving*.
2. Assess whether driver performance of the OEDR subtask *while level 2 systems are active* varies as a function of driving automation system exposure.

Research Questions

Objective 1 – Assess how driver behavior changes with exposure to the level 2 system *compared to unassisted driving*

RQ 1. How does driver's mean and minimum time-gap change as a function of automated system status and system use (exposure)?

RQ 2. Do drivers adjust their adaptive cruise control distance setting with increased exposure to driving automation?

Objective 2 – Assess whether driver performance of the OEDR subtask *while level 2 systems are active* varies as a function of driving automation system exposure.

RQ 3. What is the frequency and duration of off road glances when level 2 systems are active compared to when they are not? How do the frequency and duration of off road glances change with exposure to the driving automation systems?

RQ 4. What is the frequency and duration of instrument panel glances when level 2 systems are active compared to when they are not? Does the frequency and duration of driver glances to the instrument panel change with increased level 2 system exposure compared to unassisted driving?

RQ 5. Is there a difference in the prevalence and likelihood of secondary task engagement while the driving automation systems are active compared to when they are inactive? How does exposure to the driving automation influence driver secondary task engagement?

Hypotheses

Current training methods may be suitable to teach vehicle technology users rudimentary tasks such as how to activate systems, but users are woefully ill-equipped when it comes to their knowledge of automated driving system capabilities and limitations. It is hypothesized that drivers will accept a smaller time gap with increased experience with the driving automation system, however, a difference in their un-assisted driving time-gap is not anticipated. It is also suspected that drivers will be more likely to engage in high-risk secondary tasks and have higher eyes off road time while systems are active compared to when they are not active. While it is not yet known if these behaviors will be affected by system exposure, it is possible that as drivers become more familiar with the driving automation systems, they may feel more motivated to partake in non-driving related tasks and look away from the road for longer periods of time. It is also expected

that drivers will look at the instrument panel more frequently when the driving automation systems are active compared to when they are inactive but available because important information relating to automated system performance is located in this region.

Methods

To capture the immediate and short-term points of driver exposure to a new system mentioned by Manser (2013), the NHTSA Naturalistic Study of Level 2 Driving Automation Functions (L2 NDS) was used in these analyses.

NHTSA Naturalistic Study of Level 2 Driving Automation Functions (L2 NDS)

Russell et al. (2018) recruited 121 participants from the Washington, DC, region, which included both northern Virginia and Maryland suburbs to participate in the L2 NDS. There were ten research vehicles used in this study comprised of five makes and models; see Russell et al. (2018, p. 11) for a list of vehicles. This research effort was specifically interested in the 25 participants who drove the 2015 Tesla Model S P90D AWD with Autopilot (software version 8.0[1]). The Autopilot software package was the most up-to-date version at the beginning of data collection. Participants were between the ages of 25 and 54 and were enrolled in the study for four weeks. Participants were compensated up to $500 for full participation in the study. During recruitment, participants were asked if they owned any of the vehicles used in the study to ensure that they were not assigned to a vehicle that they currently owned. Therefore, all participants operating Tesla model vehicles in this study were not experienced users. Participants who drove a minimum of 300 miles per week were recruited for this study. A summary of participant demographics and recruitment criteria for the original research effort is shown in Table 27.

[1] Specific release notes of the capabilities and limitations of Autopilot system software updates were not publically available at the time of this study.

Participants who used the driving automation systems for less than one hour total during their four weeks of enrollment were excluded from this analysis. The remaining 23 drivers met the inclusion criteria.

Table 27. NHTSA MFA Naturalistic Driving Study Overview

	MFA Description
N Participants	121
N Tesla Participants	25
N Tesla Participants with 1 hr. + of L2 Driving	23
Ages	25 – 54
Enrollment Duration	1 month
Prior Experience with Tesla	Not current Tesla owners May have vehicles with driving automation or have driven a Tesla vehicle in the past
Driving Exposure Requirement	300 miles per week (minimum)
Training Received	Experimenter-led demonstration & test drive

Participant Training with Driving Automation Systems. Participants received training designed to mimic the information they would receive at a dealership. The original research team developed training using a number of resources, including; their experience characterizing the study vehicles, operator's manuals, dealership site visits, OEM stakeholder feedback, and online training materials. The training outlines for the study vehicles can be found in Russell et al. (2018).

The training was developed with the intention of not being overly in-depth, but still adequately covered the use of the driving automation features. Training was kept as similar as possible across all vehicles to avoid any potential bias from training differences.

Data Sampling

Data about system status was available for 4,822 trips across the 23 participants. Kinematic data as well as system status were available for the full length of these trip files.

Exposure Based Sampling. Participant driving data was parsed by units of system exposure to the advanced vehicle systems. Driver adaptation can be quantified in terms of the magnitude of change immediately after a system change occurs (immediate adaptation) and over a prolonged use period (long-term adaptation). It is also important to consider the rate of learning. Behaviors of learning can follow a power law (Newell & Rosenbloom, 1981), meaning large changes can be seen early on, but differences are less noticeable as more experience is gained. The same has been found to be true for drivers learning to use vehicle technologies (Forster et al., 2019; Noble, 2014); to account for this our sample utilized different sampling rates based on the participant's cumulative exposure with the driving automation systems.

Cumulative driving exposure to L2 systems at speeds greater than or equal to 40 miles per hour was calculated for each participant and divided into three phases. Each phase was sampled at a different rate. Phase 1 corresponds to the immediate phase in Figure 15. Phase 1 encompassed participants' first three hours of driving exposure with the driving automation systems and was sampled using a rate of 2 samples per hour. The short term phase was divided into two parts; Phase 2 represented 3 hours to 8 hours of L2 exposure which was sampled at a rate of 1 sample per hour. Cumulative exposure to driving automation greater than 8 hours was assigned to Phase 3 which was sampled at a rate of 0.5 samples per hour. In the event a trip file contained L2 driving exposure for multiple phases, the trip file was split at the point where the exposure phase changed. This occurred for 37 trip files.

All trip segments where the subject vehicle was traveling above 40 miles per hour and the driving automation system was active or inactive but available were identified from the raw sensor data. These segments were then assigned to the appropriate L2 driving exposure bin and divided into 15 second samples. This strategy resulted in 87,433 potential samples available across 4,822

trips for the subsequent analyses.

Time Gap Analysis and Adaptive Cruise Setting Samples. Driving automation systems influence many variables of driver behavior, however, many variables do have limited merit for assessing driver performance as some of these factors more accurately describe system performance rather than driver choice. Time-gap is an important safety metric because, while it may be influenced by the driving automation system, the driver is required to accept the gap. Research has indicated that drivers' ratings of task difficulty, risk effort, and discomfort in relation to time headway was low for large time headways, these measurements increased for time gaps under two seconds (Lewis-Evans, De Waard, & Brookhuis, 2010; Tscharn, Naujoks, & Neukum, 2018). The driver can adjust system settings or choose disuse of the automation in situations where the time-gap is deemed too low to meet the operator's ideal measure of safety. It was speculated by Hoedemaeker and Brookhuis (1998), however, that the use of adaptive cruise control could lead to a shorter minimum time-gap while using driving automation compared to unassisted driving.

Trip segments identified using the exposure based sampling method (described in the previous section) were used to assess driver time gap maintenance when driving automation systems were active compared to when they were inactive, and how these behaviors changed over time with increased exposure to the systems. The 87,433 samples described in the previous section were checked to determine exceedance of radar limitations, lead vehicle presence, and turn signal activation. Samples where the radar limits were exceeded, where there was no lead vehicle identified, or a turn signal was activated (indicating an actual or possible lane change) were excluded from this analysis. Additionally, only cases where the Tesla system identified the lead object as either a Car or Truck were used in this analysis. This criterion omitted any unknown objects and vulnerable road users such as pedestrians, bicyclists, and motorcyclists from these

analyses. This resulted in 50,943 samples for the time-gap analysis (automation active: 32,711; automation available but inactive: 18,232).

The Adaptive Cruise Control (ACC) Setting Analysis used the "Automation On" samples from the time-gap analysis samples since ACC only controlled the vehicle's distance from the lead vehicle when the driving automation systems were active. Table 28 shows a breakdown of the Time Gap samples by Exposure Phase

Table 28. Time Gap Samples by Phase

Phase	Automation Status		Total
	Inactive	Active	
PHASE 1	7,579	8,689	16,268
PHASE 2	7,033	12,026	19,059
PHASE 3	3,620	11,996	15,616
Total	18,232	32,711	50,943

Eyes off Road and Secondary Task Samples. 556 epochs with a duration of 15 seconds were sampled for eye glance behavior and secondary task analysis. The same data reduction protocol to that presented in **Chapter 3** was followed (page 65), however, it is important to note that no context based matching occurred between cases and controls (e.g., time of day, day of week, and vehicle speed ± 5 miles per hour). While baseline samples were selected based upon system status as collected on-board the vehicle, the status of the driving automation systems were also verified by data reductionists prior to beginning event reduction. Table 29 shows the sampling strategy for the reduced epochs and the expected cases and controls as well as the number of cases and controls used in the analysis based on the available data.

Table 29. Sampling strategy for reduced epochs

Phase	Start Hour	Stop Hour	Samples per hour	Expected Cases	Expected Controls	Actual Cases	Actual Controls
Phase 1	0	3	2	135	135	**135**	**128**
Phase 2	3	8	1	96	96	**96**	**96**
Phase 3	8	end	0.5	51	51	**51**	**50**
		N Samples Total		**282**	**282**	**282**	**274**
					N Selected Epochs	**556**	

This sample of the data was used to determine if driver eye glance behavior and secondary task engagement was different when driver assistance systems were active compared to when they were available but inactive and how these behaviors changed over time. The number of epochs per participant varied by exposure to level 2 driving automation as described previously. Each of these epochs were 15 seconds in duration and were coded for a battery of variables by trained data reductionists (for additional information see Researcher Dictionary for Safety Critical Event Video Reduction Data Version 4.2, Virginia Tech Transportation Institute (2009)).

Independent Factors

Driver behavior was hypothesized to change over time based on system exposure and perceived familiarity. Therefore, changes in user behavior over time were examined in this study. Levels of the independent variables are described below and shown in Table 30.

Table 30. Independent Factors Overview

Variable Name	Type	Description
L2 System Status	Categorical	• On: Both lateral and longitudinal vehicle motion control subtasks of the DDT were being controlled by the automated driving assistance system. • Available but Inactive: Both lateral and longitudinal vehicle motion control subtasks of the DDT were being controlled by the human driver.
Exposure Measure (Phase)	Categorical	The phases of driver exposure to level 2 driving automation systems at speeds greater than 40 miles per hour are described below and denoted by "t". • Phase 1: 0 hours < t ≤ 3 hours • Phase 2: 3 hours < t ≤ 8 hours • Phase 3: 8 hours < t

L2 System Status. L2 System Status refers to the status of the driving automation system during the epoch of interest. The driving automation system active vs. available was identified from the vehicle network. This binary categorical factor was categorized as either System Active, which indicates the driving automation system was actively maintaining lateral and longitudinal control of the vehicle, or System Inactive but available for use if the driver chose to do so. The minimum speed was 40 miles per hour for these events. Those periods of time when the L2 systems were not available for use have been removed from this analysis to ensure a valid comparison.

Exposure Measure (Phase). To assess how driver behavior changed as a function of exposure to the L2 driving automation, driver behaviors were sampled using the method described previously. Three levels of exposure were assessed in this study (referred to as Phases 1 – 3). Phase 1 encompassed participants' first three hours of driving exposure, phase 2 represented 3 hours to 8 hours, and phase 3 represents more than 8 hours of experience with the driving automation system.

Dependent Measures

The following dependent measures were used to answer the research questions described

on page 86.

Time-Gap. Time gap is calculated by dividing the following distance (ΔX), collected from the vehicle's radar unit, by the subject vehicle's velocity (μ) (Hammit, Ghasemzadeh, James, Ahmed, & Young, 2018). The units for distance are meters and the subject vehicle's velocity is in meters per second. Gap is included in this research effort due to the fact that prior research has demonstrated that it is an important factor when drivers initiate braking and it also influences how drivers control braking (McLaughlin, 1998).

Table 31 describes the dependent measures used for time-gap in this study. It is important to note, due to the limitations of the Tesla system radar and speed threshold the maximum time-gap for these analyses did not exceed 7 seconds.

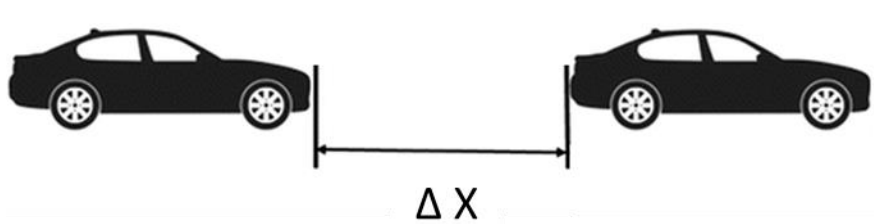


Figure 16. Depiction of ΔX for computing time-gap

$$\boldsymbol{Gap\ [s] = \frac{\Delta X}{\mu}} \qquad \textbf{(2)}$$

Table 31. Time-Gap Dependent Measures

Measure	Description
Minimum Time-Gap	Shortest time-gap recorded with respect to the lead vehicle for a 15 second epoch.
Mean Time-Gap	Average time gap recorded with respect to the lead vehicle for a 15 second epoch.

Adaptive Cruise Control Distance Setting. Tesla's adaptive cruise control had seven levels ranging between one and seven; where one was the shortest distance and seven was the most

conservative. Each setting corresponded to a time-based distance from the lead vehicle (if detected), however, the vehicle did not exceed the driver's set-speed, except for under certain conditions specified in the operator's manual (Tesla Inc., 2018). The adaptive cruise control setting remained constant between trips unless the driver chose to adjust the setting.

Eye Glance Behavior. Monitoring the roadway and determining the field of safe travel remained the responsibility of the driver when using level 2 driving automation. This is a fundamental component to the driving task and excessively long off road glances increase the odds of crash involvement (Klauer, Guo, Sudweeks, & Dingus, 2010). However, essential information about the status of the driving automation system is located on the instrument panel, therefore some glances to this region were expected. The dependent measures for eye glance behavior were divided into two categories; Off Road Glance Measures and Instrument Panel Glance Measures.

Off Road Glance Measures. Off road glance measures are described in Table 32. A detailed description of the on and off road glance locations used in this study can be found in Appendix J. Defining on Road Glance Locations.

Table 32. Eye Glance Measures

Glance Measure	Acronym	Description
Total Eyes off Road Time	TEORT	The summation of all glance durations to all AOIs other than the road scene ahead during a sample interval in seconds (SAE International, 2017).
Mean Off Road Glance Duration	MGOR	The average duration of all glances away from the road scene during the 15-second sample interval.
Single Longest off Road Glance	SLG	The duration of the single longest glance away from the road scene during the sample interval.
Number of off Road Glances	NORG	The number of glances away from the road scene during the 15-second sample interval.

Instrument Panel Glance Measures. One of the driver's responsibilities in the completion of the OEDR subtask is to supervise the driving automation system (SAE International, 2018). Key visual stimuli that were not contained in the forward roadway pertaining to automated system performance were found on the instrument panel, including system status and set speed. Therefore, glances to the instrument panel were assessed separately from the off road measures. Glance measures to the instrument panel are described in Table 33.

Table 33. Eye Glance Measures to Instrument Panel

Glance Measure	Description
Total glance duration to the instrument panel	The sum of the duration of all glances to the instrument panel during the sample interval.
Single longest glance to instrument panel	The duration of the single longest glance to the instrument panel during the sample interval.
Mean glance duration to instrument panel	The average duration of all glances to the instrument panel during the 15-second sample interval.
Number of glances to the instrument panel	This number of glances to the instrument panel during the 15-second sample interval.

Prevalence and Likelihood of Secondary Task Engagement. The method of task classification is described below in Table 34; these groupings are similar to those used by Dingus et al. (2016) where driver secondary task prevalence and their contribution to crash risk were assessed using data from the SHRP 2 Naturalistic Diving Database. In the present analysis, up to six secondary task behaviors were coded for 15-second epochs. The prevalence of secondary tasks while automation was active compared to when was inactive.

Table 34. Secondary Task Classification

Secondary Task	Disaggregate Tasks
Any Task	If secondary task 1 was populated with a task other than "No Secondary Task"
All Cellphone	All cellphone tasks
Visual-Manual Cellphone	All cellphone tasks excluding talking
Talking	Cellphone, Talking/listening, hand-held
Texting	Cellphone, Texting
Dialing	Cellphone, Dialing hand-held, including using quick keys
Browsing	Cellphone, Browsing
Reaching Phone	Cellphone, Locating/reaching/answering
Reaching for object in vehicle (non-cellphone)	Reaching for cigar/cigarette Reaching for food-related or drink-related item Interaction with moving object Reaching for object, other Tablet device, locating/reaching Reaching for personal body-related item
External Distraction	Looking at an object external to the vehicle Looking at previous crash or incident Looking at pedestrian Looking at animal Other external distraction
Passenger Interaction (adult or child)	Passenger in adjacent seat – interaction Passenger in rear seat – interaction Child in adjacent seat – interaction Child in rear seat – interaction
Hygiene	Biting nails/cuticles Combing/brushing/ fixing hair Removing/inserting/ adjusting contact lenses or glasses Other personal hygiene Applying make-up Brushing/flossing teeth Removing/adjusting clothing Removing/adjusting jewelry
Drinking (non-alcohol)	Drinking with lid, no straw Drinking with lid and straw Drinking with straw, no lid Drinking from open container
Eating	Eating without utensils Eating with utensils
Reading/Writing (includes tablet)	Reading Writing Tablet device, viewing Tablet device, other Tablet device, operating
Dancing	Dancing

Analyses

Descriptive and inferential statistics were used to assess the previously described research questions. For all analyses, statistical significance was evaluated at $\alpha = 0.05$. All models except where explicitly noted include a driver-specific random effect term which incorporates the correlations among observations from the same driver.

Assessments of driver's minimum and mean time gap were performed using a mixed general linear model with a random driver effect term and nested trip level covariate. These random effects allowed for the model to account for correlations among observations from the same driver within the same trip. This analysis was performed to understand if and how driver's time-gap maintenance changes while using the driving automation systems and with exposure to the system. The dependent factors were assessed by automation system status (active, inactive) and L2 driving automation exposure (Phase 1, Phase 2, Phase 3). The interaction of automation status and automation exposure was also assessed by the dependent variable.

Additionally, the assessment of the drivers' time-gap selection on the adaptive cruise control system while the driving automation system was active was performed to corroborate any findings from the time gap analysis. Multiple logistic regression models were used to assess ACC Distance Setting. The dependent measure of ACC Distance Setting was dummy coded for the distance of interest (e.g., Distance 5 = 1) while all other distances were set to 0. Driver random effects and trip level covariates were included in the model to account for correlations among observations from the same driver within the same trip. This analysis allowed for the assessment of the likelihood of a particular time-gap selection within a given exposure phase while the driver was using the driving automation system.

The driver's primary responsibility while L2 systems were active was the performance of

the OEDR subtask (SAE International, 2018). Therefore, driver's eye glance behavior both to the driving scene and to the instrument panel were assessed. Generalized linear mixed-models with the driver-specific random effect were used assess the duration (TEORT, SLG, and MGOR) and frequency of glances away from the road scene (NORG). Independent factors include automation status, exposure phase, and the interaction between these two effects. Each dependent variable was evaluated in a separate model.

The likelihood of high-risk secondary task engagement was assessed using a mixed effects logistic regression with random driver effect term, In the event that the mixed-effects model was unable to converge, a conventional logistic regression was used. The dependent factor of secondary task engagement (Yes/No) was evaluated by the main effects of driving automation status (active, inactive) and automation exposure (Phase 1, Phase 2, Phase 3) and their interaction.

Table 35 shows the research plan for this study. The research question along with the associated independent and dependent measures are shown with the specified analysis.

Table 35. Overview of Study 3 Research Plan

Objective	Research Question	Dependent Measures	Independent Measures	Analysis
DRIVING STYLE	RQ 1. How does driver's mean and minimum time-gap change as a function of automated system status and system use (exposure)?	Mean time-gap Minimum time-gap	System Status Phase	Generalized Linear Mixed-Model with driver and trip random factor
DRIVING STYLE	RQ 2. Do drivers adjust their adaptive cruise control distance setting with increased exposure to driving automation?	ACC Distance Setting	Phase	Mixed-Effects Logistic Regression with driver and trip random factor
OEDR	RQ 3. What is the frequency and duration of off road glances when level 2 systems are active compared to when they are not? How do the frequency and duration of off road glances change with exposure to the driving automation systems?	TEORT MGOR SLG NORG	System Status Phase	Generalized Linear Mixed-Model with driver random factor
OEDR	RQ 4. What is the frequency and duration of instrument panel (IP) glances when level 2 systems are active compared to when they are not? Does the frequency and duration of driver glances to the instrument panel change with increased level 2 system exposure compared to unassisted driving?	Total glance duration to IP Mean glance to IP SLG to IP N Glances to IP	System Status Phase	Generalized Linear Mixed-Model with driver random factor
OEDR	RQ 5. Is there a difference in the prevalence and likelihood of secondary task engagement while the driving automation systems are active compared to when they are inactive? How exposure to the driving automation influence driver secondary task engagement?	High Risk Secondary Task Engagement (Yes/No)	System Status Phase	Mixed Effects Logistic Regression with driver random factor

Results

23 volunteer drivers (12 male), were included in this analysis. The mean participant age was 39.7 (SD=7.2) years old. Over 44,000 miles of driving data was recorded for 1,514 hours; 245

hours (15,830 miles) of driving exposure took place while using L2 driving automation at speeds above 40 miles per hour. Figure 17 shows the distribution of cumulative exposure to driving automation systems above the 40 mile per hour threshold for each participant during their enrollment in the study. The average duration of L2 system use above 40 miles per hour was 10.66 hours (SD = 5.20 hours). Additional information about participant driving exposure for these data is located in Appendix L. Participant Driving Exposure.

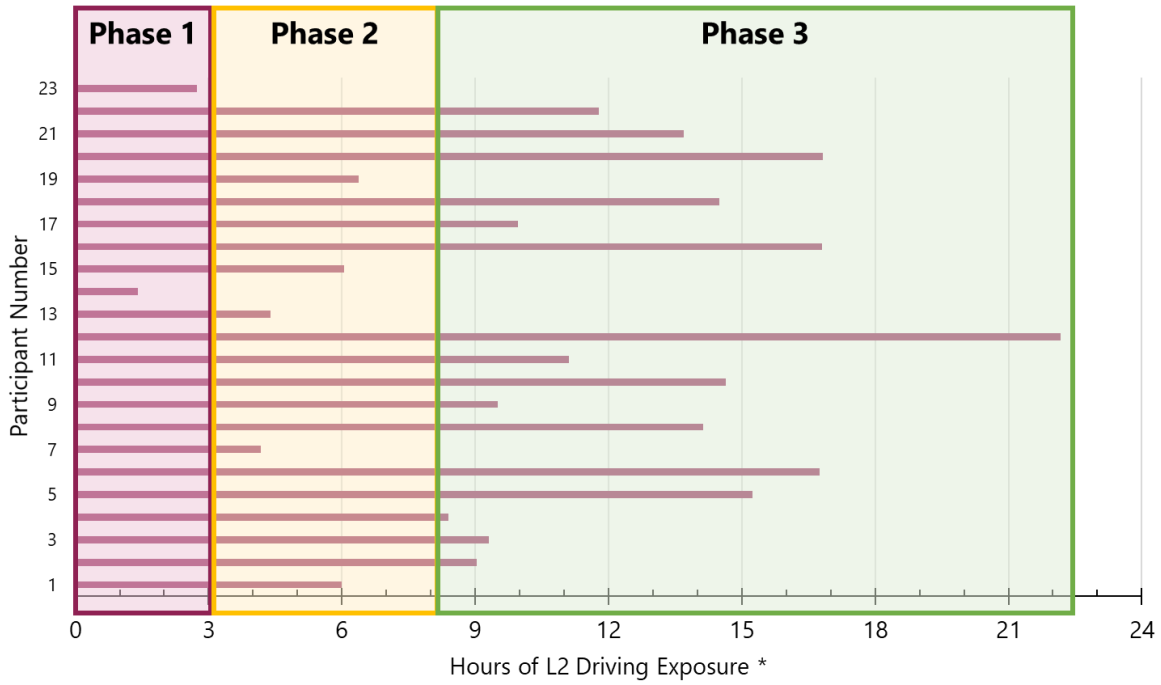


Figure 17. Distribution of participant exposure to L2 systems at speeds greater than or equal to 40 miles per hour while enrolled in the study.

Minimum Time-Gap

A mixed effects general linear model with random driver effect was used to understand if a relationship between minimum time-gap and exposure to driving automation existed. The main effect of automation [F(1, 48886)=1.36, p=0.2440] was not significant. The main effect of phase [F(2,48886)=4.06, p=0.0172] and the interaction of automation status and phase were significant for minimum time-gap [F(2, 48886)=3.39, p=0.0338]. Tukey's post hoc test revealed that there was a significant difference when the automation was active between Phase 1 (M=1.39, SD=0.97)

and Phase 3 (M=1.29 SD= 0.92). There was also a significant difference in the time-gap when automation was active between Phase 2 (M=1.39, SD=0.99) and Phase 3 (M=1.29 SD= 0.92). Model solutions and retrospective power analyses are reported in Appendix M.

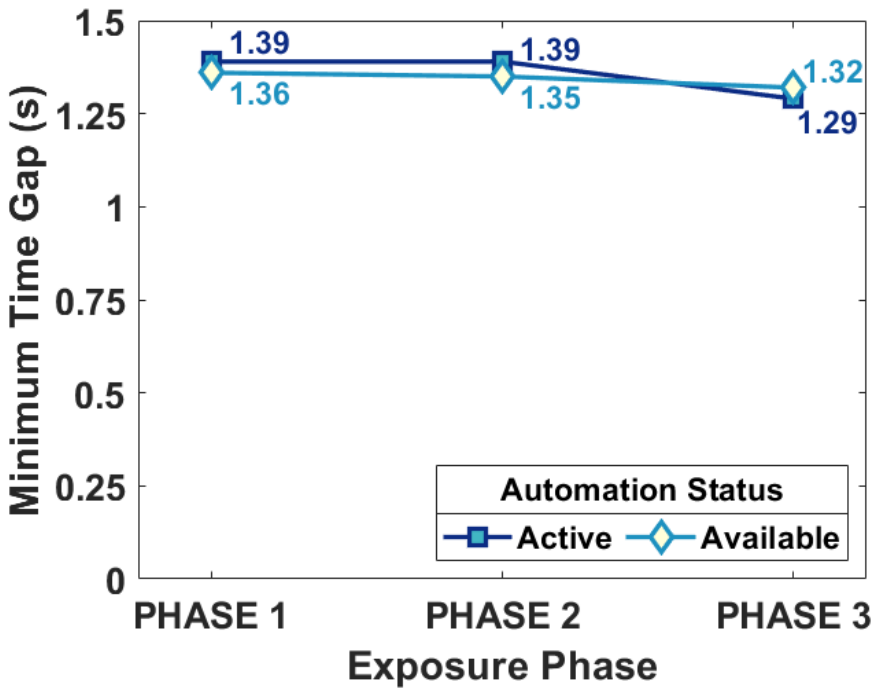


Figure 18. Minimum time-gap by exposure phase

Mean Time-Gap

A mixed effects general linear model with random driver effect was used to understand if there was a relationship between mean time-gap and exposure to driving automation. The main effects of driving automation [F(1, 48886)= 0.01, p= 0.9358] and phase [F(2, 48886)=1.93, p=0.1454] did not have a significant effect on mean time-gap. There was a significant interaction of automation status and phase for mean time-gap [F(2, 48886) =8.73, p=0.0002]. While driver's mean time-gap remained relatively consistent over time while the driving automation was inactive (Figure 19), the mean time-gap varied while the driving automation system was active with significant differences occurring between Phase 1 (M=1.88, SD=1.17) and Phase 3 (M=1.77, SD=1.14) as well as Phase 2 (M=1.90, SD=1.20) and Phase 3 (M=1.77, SD=1.14). There was no

significant difference between driver time gap when automation was active within Phase 1 (M=1.88, SD=1.17) and Phase 2 (M=1.90, SD=1.20). There was no significant difference between Phase 3 Automation active (M=1.77, SD=1.14) and Phase 3 Automation inactive (M= 1.83, SD=1.17). Model solutions and retrospective power analyses are reported in Appendix N.

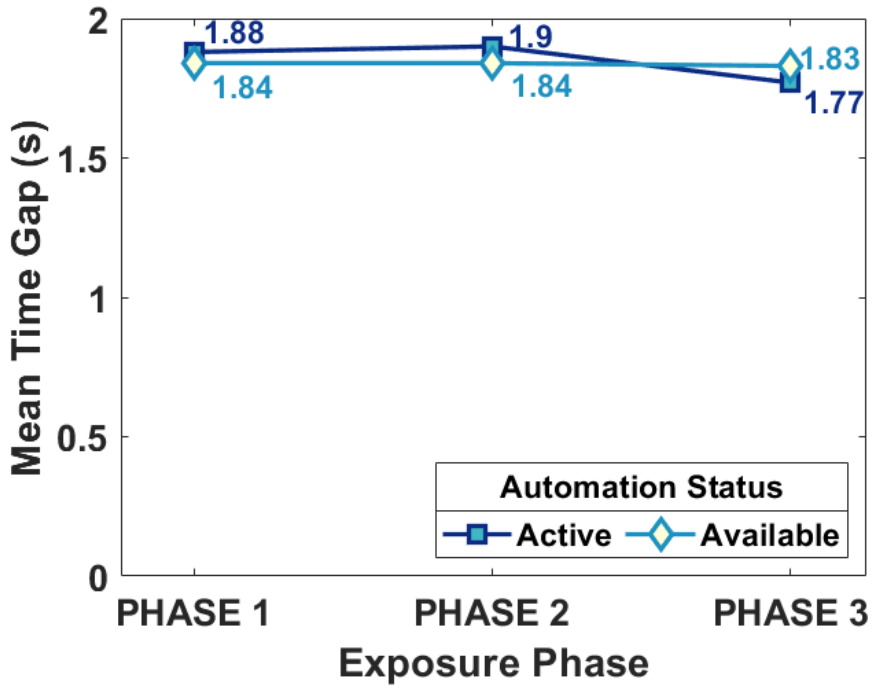


Figure 19. Mean time-gap by exposure phase

ACC Distance Setting

To investigate whether the settings of the driving automation system contributed to the changes in the mean-time gap observed in the previous analysis an assessment of the driver's ACC Distance settings was conducted. Multiple logistic regression models were used to assess ACC Distance Setting. The dependent factor of ACC Distance was dummy coded for the distance of interest (e.g., Distance 5 = 1) while all other distances were set to 0. This method allowed the determination of the likelihood of a particular distance setting being chosen during a given exposure phase. Note that Distances 6 and 7 were excluded because they were not used by participants. Table 36 shows the solutions for the logistic regression models. Drivers were more

likely to select Distance 5 compared to other distances in Phase 2 (OR: 1.78, [CI: 1.58, 2.00]) and Phase 3 (OR: 2.48, [CI: 2.20, 2.79]) as compared to Phase 1. Interestingly, Distance 1 was also more likely to be chosen by drivers in Phase 3 compared to Phase 1 (OR: 1.37, [CI: 1.28, 1.47]). This indicates that driver preference for time-gap setting is non-uniform. Some drivers prefer a shorter time-gap while others prefer a longer time-gap. Over time it appears drivers were more likely to fall into one of these two groups as indicated by the results for the intermediate time-gap distances (e.g., Distance 2, 3, and 4) which indicated that drivers were less likely to select these distances in their later exposures compared to their earlier experiences.

Table 36. Odds Ratios for ACC Distance Setting by Phase. Distances 6 and 7 were excluded because they were not used by participants.

	ACC Distance	Phase	Reference	OR	+/-	DF	LL	UL	Sig
Longer	Distance 5	PHASE 2	PHASE 1	1.78	+	32,686	1.58	2.00	*
		PHASE 3	PHASE 1	2.48	+	32,686	2.20	2.79	*
	Distance 4	PHASE 2	PHASE 1	1.13	+	32,686	1.04	1.23	*
		PHASE 3	PHASE 1	0.36	-	32,686	0.32	0.40	*
	Distance 3	PHASE 2	PHASE 1	0.93		32,686	0.86	1.00	
		PHASE 3	PHASE 1	0.74	-	32,686	0.68	0.81	*
	Distance 2	PHASE 2	PHASE 1	0.79	-	32,686	0.74	0.84	*
		PHASE 3	PHASE 1	1.01		32,686	0.95	1.09	
	Distance 1	PHASE 2	PHASE 1	1.02		32,686	0.96	1.09	
Shorter		PHASE 3	PHASE 1	1.37	+	32,686	1.28	1.47	*

Figure 20 shows the percentage of driver distance selection over time. Participants used the shortest time-gap distance most often regardless of exposure phase. Drivers used the shortest time gap setting most often in Phase 3 (34.3%) compared to Phases 1 (31.5%) and 2 (31.2%). Interestingly, the prevalence of Distance 5 more than doubled between Phase 1 (6.6%) and Phase 3 (13%) indicating that driver preferences for system use over time are non-homogenous.

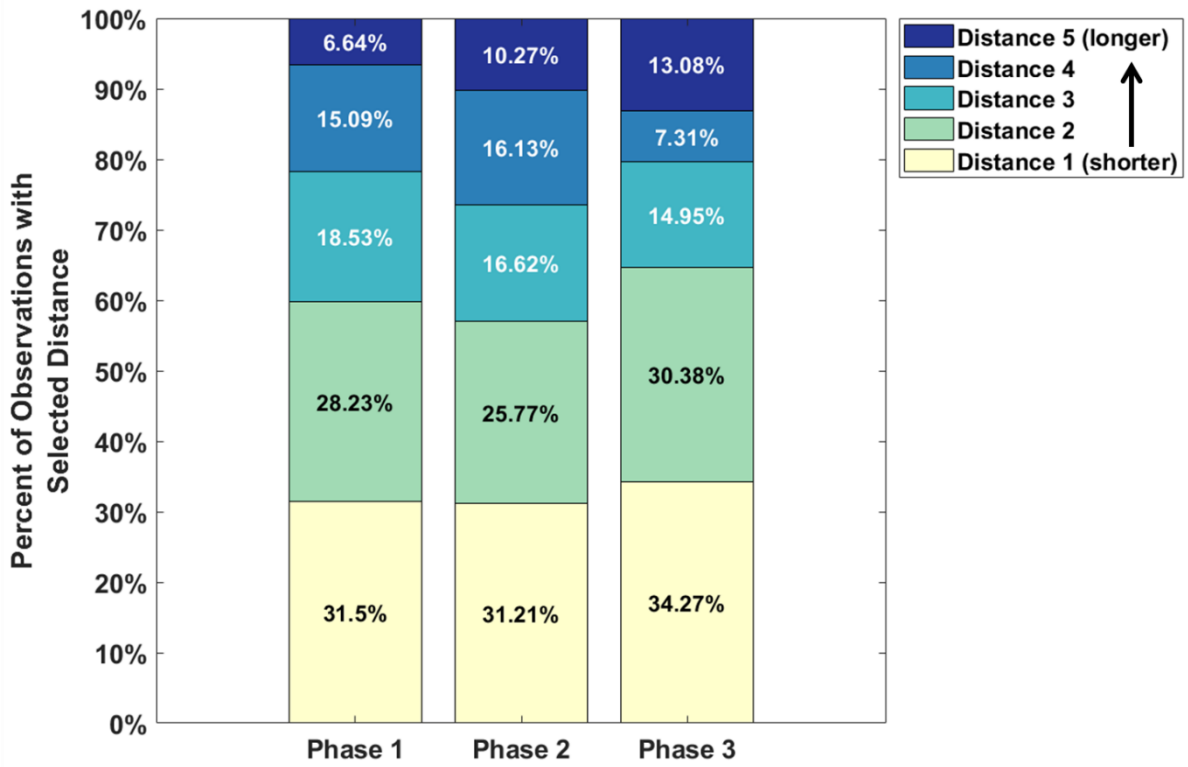


Figure 20. ACC set distance by exposure phase. Distances 6 and 7 were excluded because they were not used by participants.

Further investigation of individual driver selection of ACC Distance over time (shown in Appendix O) graphically represents the ACC distance selection by exposure phase for 21 of the 23 participants. The observations for the two remaining participants were limited to Phase 1, and therefore, no exposure based comparison was made. Ten participant's preference for their ACC distance setting ultimately settles on a shorter ACC distance setting in their later exposure phase. Four participants appear to tend toward the higher ACC distance settings over time, while six participants have no discernable pattern between their initial exposure period and final exposure period. This is further evidence of that driver preferences for system use over time are non-uniform. Preferences for system settings can vary not only between drivers, but within the same driver.

Eye Glance

A total of 556 epochs were used to assess driver eye glance behavior while the automation systems were active (n=282) compared to when they were inactive but available (n=274), and how these glance behaviors changed over time (phase).

Off Road Glances. Off road glances did not include glances to the instrument panel. Since pertinent system monitoring information was located on the instrument panel, these glances were considered "on road" and are also analyzed separately in the following section. The results from the mixed-effects general linear regression indicate that automation had a significant effect on all driver off road glance behavior for all measures except NORG. Interestingly, there were no differences with respect to phase or the interaction between automation and exposure phase. While no significant differences emerged, notable trends of the interaction of automation status and exposure phase are discussed below. Table 37 summarizes the differences for each dependent measure by automation status and exposure phase. Model solutions and retrospective power analyses are reported in Appendix P.

The status of driving automation system contributed to TEORT [F(1, 528)= 8.24, p=0.0043]. When driving automation was active, drivers had a higher TEORT (M=2.97, SD=2.95) than when automation was available (M=2.36, SD=2.18). TEORT appeared to increase with driving automation exposure when systems were active. The main effect of driving automation status also contributed to the MGOR duration [F(1, 528) = 9.56, p=0.0021]. When automation was active drivers had a higher MGOR (M=0.73, SD=0.60) than when the system was available (M=0.60, SD=0.40). Additionally, driving automation status contributed to the SLG [F(1, 528)=11.59, p=0.0007]. Drivers' single longest glance from the roadway with driving automation active was on average 1.17 seconds (SD=1.18), with a maximum of 10.61 seconds away from the

road. When driving automation was available, but inactive, the single longest glance was on average 0.90 seconds (SD=0.65) and the maximum single longest glance was 3.87 seconds.

The number of glances away from the roadway was not significantly impacted by automation status [F(1, 528)=0.01, p=0.9370]. When automation was active participants took an average of 3.45 glances away from the road (SD=2.60) and when the system was inactive, but available drivers took 3.40 glances away from the road (SD=2.78).

Table 37. Off Road Glance Measures by Exposure Phase and System Status

Measure	Phase	System Status	N	Mean	SD	SE	Min	Max
TEORT	Phase 1	Active	135	2.73	2.74	0.24	0	12.81
		Available	128	2.29	2.2	0.19	0	9.14
	Phase 2	Active	96	3.08	3.24	0.33	0	12.88
		Available	96	2.34	2.22	0.23	0	9.14
	Phase 3	Active	51	3.38	2.9	0.41	0	11.35
		Available	50	2.6	2.1	0.3	0	8.61
MGOR	Phase 1	Active	135	0.71	0.64	0.05	0	5.74
		Available	128	0.6	0.45	0.04	0	2.94
	Phase 2	Active	96	0.71	0.6	0.06	0	3.22
		Available	96	0.59	0.34	0.03	0	1.43
	Phase 3	Active	51	0.79	0.46	0.06	0	2.3
		Available	50	0.6	0.37	0.05	0	1.62
SLG	Phase 1	Active	135	1.09	1.23	0.11	0	10.61
		Available	128	0.88	0.69	0.06	0	3.87
	Phase 2	Active	96	1.2	1.23	0.13	0	6.27
		Available	96	0.87	0.54	0.06	0	2.34
	Phase 3	Active	51	1.34	0.92	0.13	0	3.87
		Available	50	1	0.73	0.1	0	3
NORG	Phase 1	Active	135	3.39	2.56	0.22	0	12
		Available	128	3.2	2.65	0.23	0	13
	Phase 2	Active	96	3.41	2.75	0.28	0	13
		Available	96	3.46	2.92	0.3	0	12
	Phase 3	Active	51	3.71	2.45	0.34	0	9
		Available	50	3.78	2.82	0.4	0	11

While the interaction of automation status and exposure phase was not statistically significant in these analyses, a trend of increased off road glance duration with increased exposure

to the driving automation systems may be emerging (Figure 21 - Figure 24). In general it appears that as drivers have increased exposure with the driving automation systems their visual monitoring of the driving environment declines.

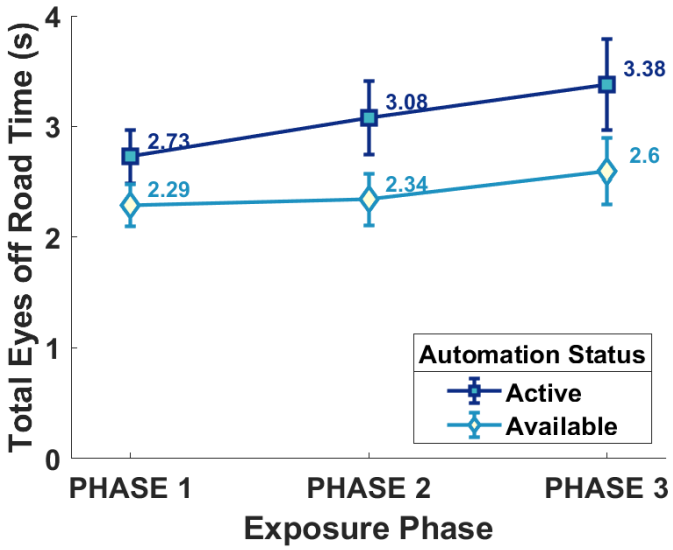


Figure 21. This figure shows participants' TEORT by driving automation status and exposure phase. The main effect of automation status was significant, drivers tended to look away from the road longer when the driving automation was active compared to when it was available. (Error bars represent standard error.)

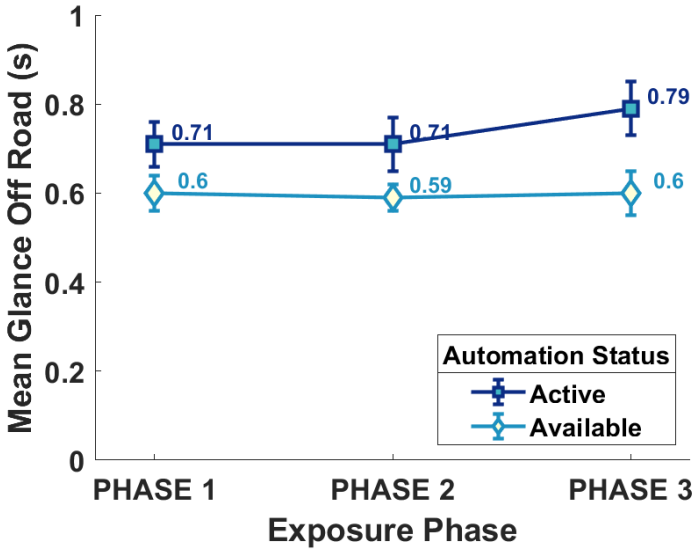


Figure 22. This figure shows participants' MGOR by driving automation status and exposure phase. The main effect of automation was significant for the MGOR analysis. (Error bars represent standard error.)

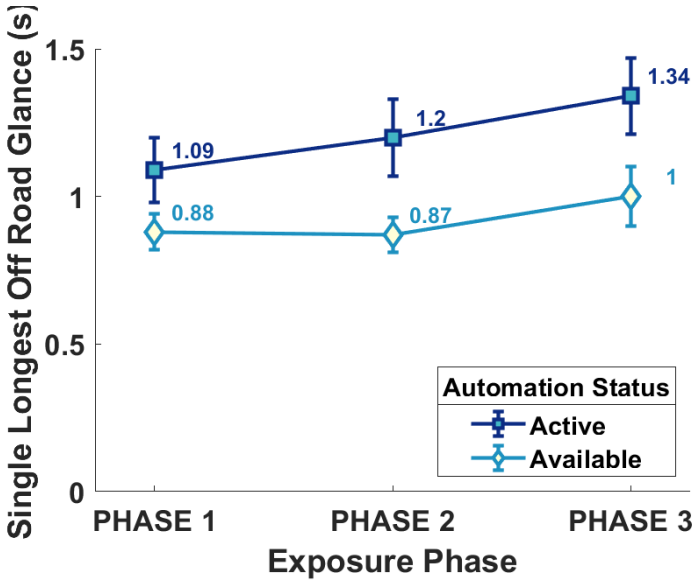


Figure 23. This figure shows participants' SLG by driving automation status and exposure phase. The main effect of automation was significant for the SLG analysis. (Error bars represent standard error.)

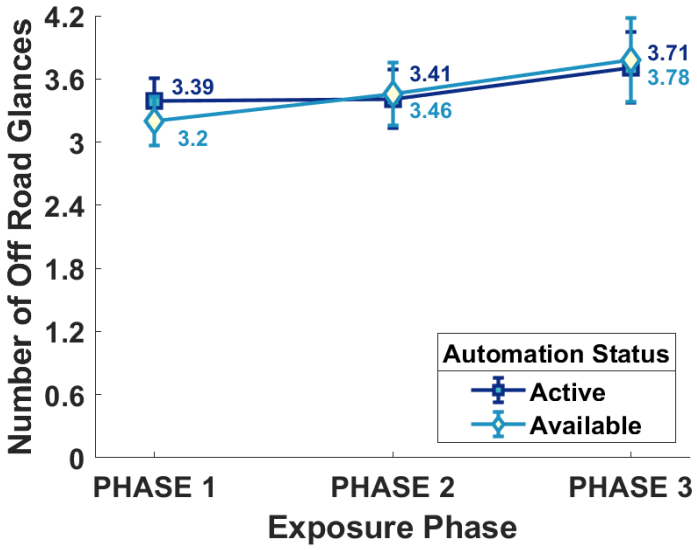


Figure 24. This figure shows participants' number of off road glances by driving automation status and exposure phase. Neither main effect nor their interaction was statistically significant for this analysis. (Error bars represent standard error.)

Glances to the Instrument Panel. The main effect of driving automation status had a significant influence on most eye glance measures, however, no significant differences were found for the main effect of exposure phase or the interaction between automation status and exposure phase. Table 38 summarizes the differences for each dependent measure by automation status and exposure phase. Model solutions and retrospective power analyses are reported in Appendix Q.

Total glance duration to the instrument panel was not influenced by automation status [F(1, 528) =3.71, p=0.0546]; when automation was active drivers spent an average of 0.54 seconds (of the 15-second epoch) looking at the instrument panel (SD=0.89 s). When the driving automation was inactive drivers looked at the instrument panel for 0.40 seconds on average (SD=0.81).

Drivers' mean glance duration to the instrument panel was impacted by automation status [F(1, 528) = 6.44, p= 0.0114]. Drivers mean glance duration to the instrument panel while the driving automation was active was 0.31 seconds (SD=0.40) and 0.22 seconds when the system was inactive (SD=0.35) when the systems were inactive but available.

Drivers' single longest glance to the instrument panel was influenced by the automation status [F(1, 528)=4.83, p=0.0283]. When the driving automation systems were active, drivers' single longest glance to the instrument panel was 0.36 seconds on average (SD=0.49). However, when the driving automation systems were inactive, the average single longest glance to the instrument panel was 0.26 seconds (SD=0.45). The status of the driving automation system also influenced the number of glances to the instrument panel [F(1, 528)= 4.02, p=0.0454]. When the driving automation systems were active, drivers made on average 0.79 glances to the instrument panel (SD=1.13). When the system was not active but available, drivers made an average of 0.61 glances to the instrument panel (SD=1.11).

Table 38. Glances to the instrument panel

Measure	Phase	System Status	N	Mean	SD	SE	Min	Max
Total glance duration to the instrument panel	Phase 1	Active	135	0.57	0.86	0.07	0	4.67
		Available	128	0.45	0.9	0.08	0	5.14
	Phase 2	Active	96	0.51	0.91	0.09	0	4.54
		Available	96	0.32	0.66	0.07	0	3.47
	Phase 3	Active	51	0.54	0.94	0.13	0	5.07
		Available	50	0.42	0.84	0.12	0	4.54
Mean glance duration to instrument panel	Phase 1	Active	135	0.34	0.39	0.03	0	1.54
		Available	128	0.24	0.38	0.03	0	1.8
	Phase 2	Active	96	0.28	0.42	0.04	0	2.47
		Available	96	0.18	0.32	0.03	0	1.4
	Phase 3	Active	51	0.28	0.38	0.05	0	1.23
		Available	50	0.21	0.33	0.05	0	1.27
Single longest glance to instrument panel	Phase 1	Active	135	0.39	0.45	0.04	0	1.8
		Available	128	0.3	0.5	0.04	0	2.4
	Phase 2	Active	96	0.34	0.54	0.05	0	2.67
		Available	96	0.21	0.36	0.04	0	1.47
	Phase 3	Active	51	0.33	0.5	0.07	0	2.14
		Available	50	0.27	0.44	0.06	0	1.87
Number of glances to the instrument panel	Phase 1	Active	135	0.85	1.12	0.1	0	5
		Available	128	0.65	1.13	0.1	0	7
	Phase 2	Active	96	0.71	1.14	0.12	0	6
		Available	96	0.53	1.05	0.11	0	7
	Phase 3	Active	51	0.76	1.16	0.16	0	5
		Available	50	0.68	1.22	0.17	0	6

The interaction between automation status and exposure phase were not statistically significant as shown in Figure 25-Figure 28.

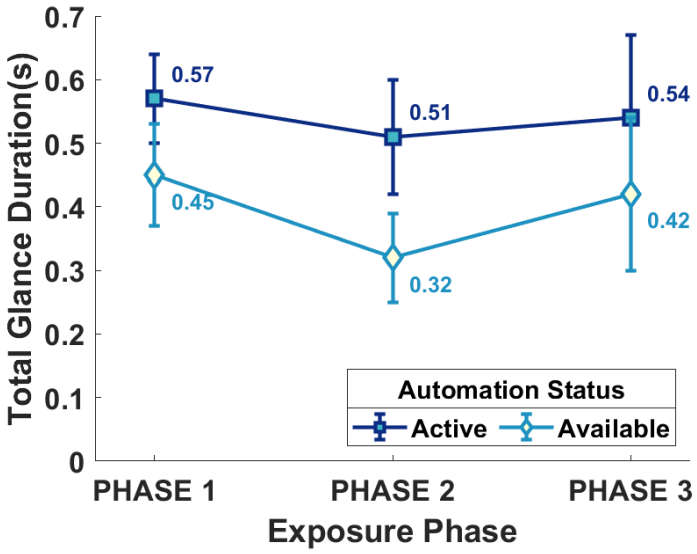


Figure 25. This figure shows participants' total glance duration to the instrument panel for the 15-second epoch by driving automation status and exposure phase. Neither main effect nor their interaction was statistically significant for this analysis. (Error bars represent standard error.)

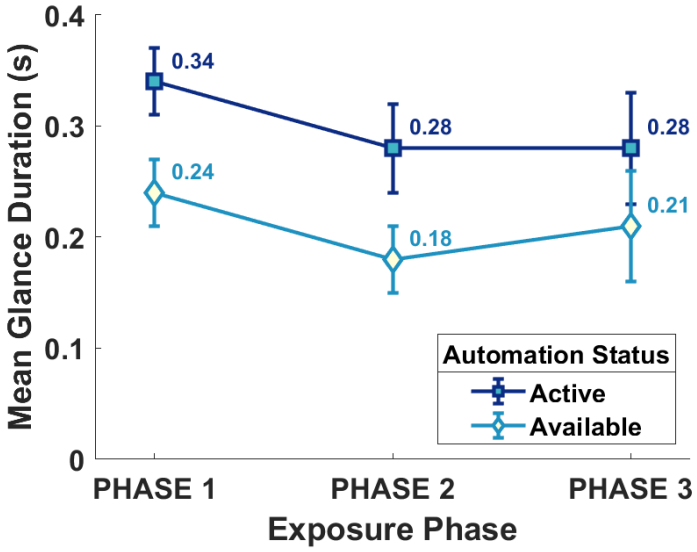


Figure 26. This figure shows participants' mean glance duration to the instrument panel by driving automation status and exposure phase. The main effect of automation was significant for this analysis. (Error bars represent standard error.)

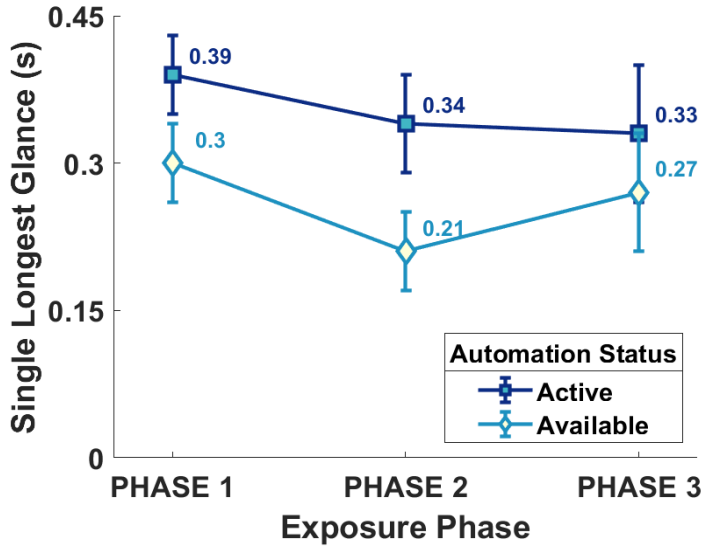


Figure 27. This figure shows participants' single longest glance duration to the instrument panel by driving automation status and exposure phase. The main effect of automation was significant for this analysis. (Error bars represent standard error.)

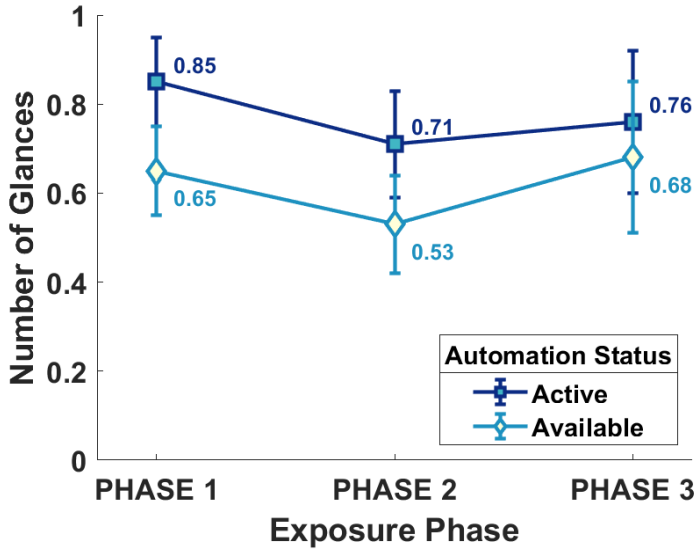


Figure 28. This figure shows the number of glances to the instrument panel by driving automation status and exposure phase. The main effect of automation was significant for this analysis. (Error bars represent standard error.)

Secondary Task

The results of the mixed-effects logistic regression did not yield any significant differences in a drivers' likelihood to perform a secondary task when the driving automation system was active or inactive but available or during each exposure phase. Table 39 shows the secondary task prevalence while automation was available and active as well as the odds ratios for tasks with computable odds ratios. The low prevalence of certain tasks (e.g., texting, dialing, and reaching) led to wide confidence intervals, therefore, only prevalence will be reported and discussed.

Interaction with passengers was among the most common secondary tasks observed whether automation was active (67.0%) or inactive but available (69.0%). Cellphone tasks were also highly prevalent among both driving situations, when automation was available (12.4%) and when automation was active (10.3%). Visual-manual cellphone tasks and other high-risk secondary tasks for adult drivers, such as external distractions and reaching for an object, were not significantly different by automation status or by time. The odds ratios for secondary tasks by phase are reported in Appendix R.

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Table 39. Prevalence and Odds Ratio Estimates for Secondary Task Engagement while Driving Automation Systems are Active compared to when they are Inactive but Available

Task	Prevalence		Odds Ratio (ref: Available)	DF	95% Confidence Interval	
	Active	Available			LL	UL
Number of observations	282	274				
Any Task	67.0%	69.0%	0.856	528	0.569	1.288
All Cellphone	10.3%	12.4%	0.714	528	0.387	1.32
Cellphone (visual-manual)	6.7%	5.8%	1.613	528	0.642	4.05
Talking (cell phone)	3.9%	6.9%				
Texting	0.7%	0.0%				
Dialing	0.4%	0.0%				
Browsing	5.0%	4.4%				
Reaching Phone	1.1%	0.7%				
Reaching for object in vehicle (non-cellphone)	1.8%	0.7%				
External Distraction	6.0%	6.2%	0.956	528	0.47	1.946
Passenger Interaction	24.5%	24.8%	0.895	528	0.549	1.458
Drinking	2.13%	1.46%				
Eating	1.77%	0.36%				
Hygiene	3.9%	3.6%	1.120	528	0.451	2.781
Reading/Writing (includes tablet)	0.0%	0.0%				
Dancing [a]	2.1%	0.7%	76.435	550	<0.001	>999.9

[a] Indicates conventional logistic regression was used.

Discussion

The SAE Levels of Automation attempt to categorize the driving task into the constituent subtasks and allocate roles and responsibilities to the human operator and driving automation system. In this study we examined two components of the driving subtask – longitudinal control through time-gap maintenance, and object detection and response (OEDR) through eye glance behavior and secondary task engagement. The results of this study demonstrate that driver time-gap is influenced by driving automation system status and experience with the system and there is an indication of trends for increased eyes off road time and glances to the instrument panel with increased exposure to the driving automation systems.

There is evidence to suggest that drivers' minimum and mean time gap is influenced by driving automation system status and experience with the systems. This analysis showed that drivers' mean time gap varied while the driving automation systems were active with significant differences occurring between Phase 1 (0-3 hours of driving exposure) and Phase 3 (more than 8 hours of exposure) as well as Phase 2 (3 – 8 hours) and Phase 3 (more than 8 hours). Drivers' mean time gap while the driving automation systems were inactive but available remained generally consistent across their entire driving exposure (between 1.83 and 1.84 seconds). In a recent study by James and Hammit (2019) examining driver car following behavior using naturalistic driving data, the drivers' mean time gap during car following was approximately 1.87 seconds (SD=0.61) which indicates that the values observed the present work for time-gap are reasonable with respect to real-world driving conditions. These differences between automation status and exposure, however, are relatively small and while they may be statistically significant do not appear to offer much practical significance.

The analysis of ACC Distance Settings indicated that drivers used the shortest time gap setting most often in Phase 3 (34.3%) compared to Phases 1 (31.5%) and 2 (31.2%). Interestingly, the prevalence of Distance 5, the longest time-gap setting observed, more than doubled between Phase 1 (6.6%) and Phase 3 (13%), indicating that driver preferences for system use over time may be non-homogenous.

Driver off road glance behavior was influenced by driving automation system status – drivers looked away from the road longer while driving automation was active compared to when it was available. This is consistent with the results presented in **Chapter 3**. While no significant differences were found when examining the interaction between driving automation status and exposure to the driving automation system, off road glance durations did tend to increase as

drivers' gained experience with the L2 systems. Drivers adapt their glance behavior when using automated systems, which may limit the information sampling from their surroundings. In a study of automated parallel parking systems, drivers spent less time looking at the parking space when using automation than when not using automation. Additionally, the proportion of glances as well as the amount of time spent looking at the instrument cluster increased (Kidd, Reimer, Dobres, & Mehler, 2017).

When examining the frequency and duration of driver glances to the instrument panel by automation status it was unsurprising to find that the driving automation status had a significant influence on most off road glance measures, with the exception of total duration of glances to the instrument panel. While the interaction between driving automation status and exposure did not have a significant effect, a possible trend emerged, in which the duration of glances to the instrument panel decreased with greater L2 exposure. This could indicate that with more experience drivers become familiar with the cues associated with the driving automation system, but are verifying the system status with slightly more scrutiny when compared to conventional driving. However, the results presented in **Chapter 3** showed a contrasting finding – we found no significant difference in the total duration of glances to the instrument panel, mean glance duration, or the single longest glance to the instrument panel when the automation was active compared to when it was inactive. These differences indicate that a longer observation period than what was attained from the data presented in this chapter may be required to observe driver glances to the instrument panel return to their unassisted durations.

Driver performance of secondary tasks is high. While drivers are not more likely to perform a secondary task while the driving automation system is active (66.7%) compared to when it is available but inactive (68.6%) [OR: 0.837, (CI: 0.555, 1.264)] the prevalence of secondary task

engagement in previous studies has not exceeded 55% overall (Dingus et al., 2016; Guo et al., 2017; **Chapter 3**). Dingus et al. (2016) used a six second baseline sample and found overall secondary task prevalence to be 51.93% and the research presented in **Chapter 3** used a 10 second sample window and found secondary task prevalence to be 55.4%. However, in some cases the prevalence of events is more than double what is reported – tasks such as dialing, talking, browsing, reaching for a non-cellphone object, drinking (non-alcohol), and hygiene. These differences in prevalence could be attributed to a number of factors.

One hypothesis is that these differences are due to the 15 second reduction window used in the analysis (Russell et al., 2018), this could be a result of the loss of the homogeneity assumption of driver behavior in longer secondary task epochs as these windows become wider (i.e., the likelihood of observing a driver engaging in any secondary task during a six second window is lower than observing a driver engaging in any secondary task during a 15-second window). Another possible reason could be the users' perception of the vehicle's capabilities, which was not assessed in this study. The technology and reputation of a vehicle and/or driving automation system may change user expectations for performance and therefore behavior (Abraham, Seppelt, Mehler, & Reimer, 2017). Finally, the vehicles in this study were leased vehicles which have been shown to affect driver risk taking, as opposed to the research presented in **Chapter 3** which involved personal vehicles. One notable example is provided by Dingus et al. (2006), where the relative risk for drivers participating in the 100 Car Naturalistic Driving Study was examined for four weeks driving a leased vehicle driving compared to four weeks of driving their private vehicle. The results indicated that when the same driver switched from a private vehicle to a leased vehicle there were more events (crashes, near crashes, and incidents) per mile in the leased vehicle compared to the private vehicle.

The following limitations should be considered when interpreting the results of this study. This dataset was limited to a sample of drivers who lived or worked in the Northern Virginia or DC area and therefore may not have been representative of all drivers. Additionally, this participant cohort was likely to exclude drivers of inordinate risk. The driving history check performed excluded participants with certain driving violations (such as driving while intoxicated), and drivers with more than three driving violations in the past 5 years. This check was required due to University policy in order to insure the vehicles for the duration of the study. Regardless, clear cases of distraction were observed both with and without the driving automation systems active. This study is focused on driver behavior with L2 systems at speed greater than or equal to 40 miles per hour. The results of this work should not be extended to driver behavior at lower speeds. Participants were driving vehicles that were unfamiliar to them and drove them for a relatively short duration (4 weeks) compared to previous NDSs where the enrollment duration was months or years. As with most human subjects research, the sample consisted of volunteer drivers which introduces self-selection bias.

The results of this study demonstrate longitudinal control tasks, such as time-gap, change with increased exposure to driving automation systems. While no statistically significant differences were observed for eye glance measures, over time trends did emerge. Future studies should consider longer data collection periods of drivers using unfamiliar vehicle technologies to allow drivers to become familiar with the vehicles and behavioral changes to stabilize and when possible, instrument participants' own vehicles as opposed to study provided vehicles.

Chapter 5. Training Guidelines for Driving Automation Systems

A generally accepted definition of training, particularly relevant within the context of this work, is that it is a continuous and systematic process that teaches individuals a new skill or behavior to accomplish a specific task (Salas, Wilson, Priest, & Guthrie, 2006). This definition is particularly relevant to the domain of driving automation systems because drivers must become proficient in a wide variety of tasks required to operate these technologies. However, the scope of the definition focuses solely on tasks and fails to acknowledge that the use of driving automation requires proficiency in tasks that rely on and interact with driving environments (e.g., lane markings that support lane keeping assist systems [LKAS]). Therefore, a more recent training definition may be more applicable. This definition describes training as the "systematic acquisition of knowledge, skills, and attitudes that together lead to improved performance in a specific environment" (Grossman & Salas, 2011). A successful training method will impart the necessary knowledge, skills, and attitudes related to the partnership between vehicle technology and humans to promote improvements in driving performance and safety.

With this definition in mind, there are at least three overarching goals which new training programs for driving automation systems should aim to address. First, driver training programs should seek to accommodate the growth of the driver across their stages of familiarity with the technology. This means that driver training materials should take into account the needs of the driver at their initial exposure to the driving automation systems and their needs after prolonged experience. Second, driver training should strive to create appropriate levels of trust in the driving automation systems, as appropriate levels of trust in driving automation will lead to less misuse and more appropriate use of these systems. Finally, training programs should aim to increase user acceptance of driving automation systems; society cannot reap the potential benefits of these

systems if they are not used.

Elements of Consumer Education for Driving Automation Systems

When components of the driving task become automated, new tasks are introduced that the human is responsible for performing (Bainbridge, 1983; Lee, 2017; Seppelt, Reimer, Russo, Mehler, & Fisher, 2018). Upon their initial exposure to the driving automation systems, a two pronged training approach should be considered, one that takes into account the machine and the human operator. Figure 29 provides an overview of a knowledge and skill taxonomy developed in part by Manser et al. (2019) and modified to include the role of the human driver and human-automation interaction based on the findings of this dissertation. Recommendations for how current training materials should be updated are discussed in this chapter, in the context of the taxonomy.

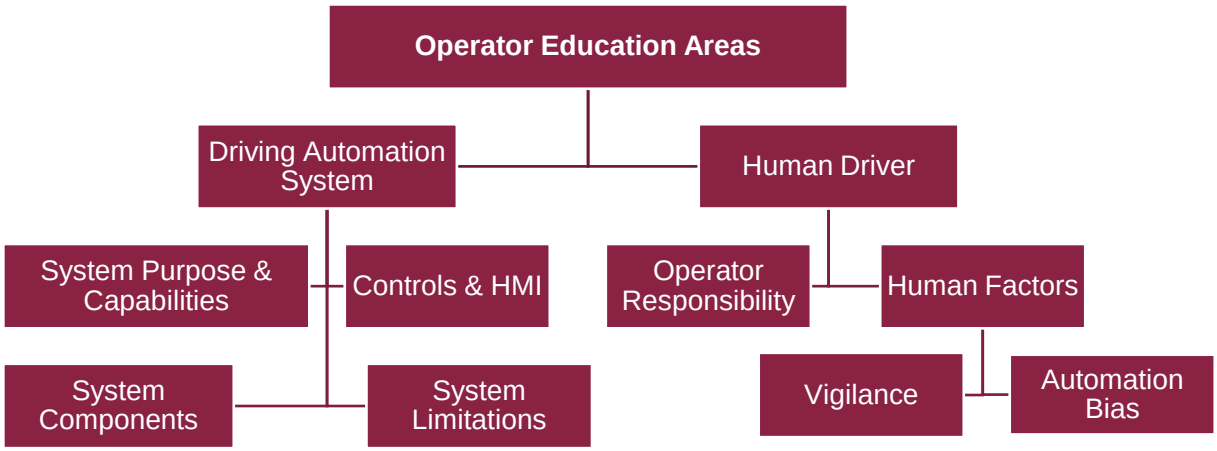

Figure 29. Knowledge and skill taxonomy of training for driving automation systems

Automation Centric Training Elements. In the traditional sense, operating a vehicle is simple, however, adding driving automation incorporates an additional layer of complexity into the driving task. Therefore, operators should be trained on the system purpose and capabilities,

automation controls and user interface, essential system components such as cameras and sensors, and the limitations of these systems.

System Purpose and Capabilities. When a member of the motoring public elects to use a driving automation system, one of the fundamental levels of knowledge that should be understood is the purpose of the system as well as any associated risks and benefits. Training drivers on this information could eliminate many negative consequences that result from the misuse of driving automation by appropriately modulating the user's expectations of the system's capabilities. Informing drivers of the function of the automated features and what they do is a primary area of concern. McDonald et al. (2018) found that for some features, 20% of owners were not sure whether or not the functions were available in their vehicles. Two areas that require further clarification are feature availability and how the naming of automated driving features influences the operator's mental models and their perception of their role in the driving task (Ankem et al., 2019; Consumer Reports, 2019b; Seppelt et al., 2018).

System Controls and HMI. In their initial exposure, drivers will need to be familiarized with the system interface, purpose, methods of activation and deactivation, and basic system signals. Moreover, according to Seppelt et al. (2018), in addition to monitoring the environment and vehicle, two fundamental skills are required to supervise the driving automation: information integration and analysis. Specifically, operators will need to be able to quickly and accurately interpret potentially high volumes of automation-generated data in real-time, as well as extract useful information from HMIs, such as system status. These skills will require intimate knowledge of the constituent displays and feedback (tones, alerts, warnings, etc.), which will require training. This could be done using the vehicle interface and multimedia methods so that auditory alerts are

consistent, as are the placement, size, shape, and color of icons pertinent to the system (similar to the experimental training described in **Chapter 2**).

System Components. Drivers need to be familiar with main components of the systems on their vehicle and know where they are located. For instance, many assistance features utilize data collected from sensors and cameras to apply throttle or braking. If these sensors or cameras are blocked, they could produce inaccurate information and unexpected system behaviors. According to McDonald, Carney, & McGehee (2018), 33% of respondents with automatic emergency braking systems did not realize that the system relied on cameras or sensors that could be blocked by dirt, ice, or snow. Given that these system components are required for appropriate function, users of these driver support and active safety features should have an understanding of when these systems can fail to operate and conditions under which it would be prudent to temporarily suspend system use. Better understanding could be achieved through the use of proper training.

System Limitations. Drivers must understand the capabilities and limitations of the driving automation system that they are using, a skill which, to date, many users have demonstrated deficiencies in through both knowledge-based tests and their own self-reported behavior. Evidence of this situation was provided by McDonald, Carney, & McGehee (2018) who found that only 21% of owners of vehicles with blind spot monitor systems correctly identified the inability to detect vehicles passing at very high speeds as a system limitation; the remainder expressed additional misconceptions about the blind spot monitor system's function and/or reported that they were unsure of the system's limitations.

Chapter 2 of the present work shows that drivers may not be familiar with limitations of the systems and demonstrated difficulty extrapolating beyond their own recall. For example, participants were able to recall the "sensors obstructed" limitation but did not indicate that dusk or

dawn would be a time where the optical sensor would struggle to detect forward vehicles. Additionally, for lane keeping assistance systems, participants were able to recall the "absence or lack of quality lane markings" being a limitation of these systems. However, this realization did not extend to work zones. This is possibly due to the diverse nature of the work zone environment, which does not necessarily always include obscured or missing lane markings. Interestingly, the results from **Chapter 3** indicated that despite users' general inability to recall and recognize system limitations, drivers were still using the driving automation systems in appropriate operational design domains in terms of vehicle speed and roadway characteristics.

The AAA Foundation for Traffic Safety, in collaboration with the Massachusetts Institute of Technology AgeLab, has developed a systematic method to review and rate the effectiveness of new in-vehicle technologies that aim to improve safety (Mehler et al., 2014). This review focuses on legacy systems, such as Electronic Stability Control, and advanced features, such as Adaptive Cruise Control, Adaptive Headlights, Back-Up Cameras, FCW, Forward Collision Mitigation, and Lane Departure Warning. In addition to developing a rating system that considers the potential and demonstrated benefits offered by these technologies, the research team stated that while some systems require little or no familiarity with the technology to derive benefit, others have a steep learning curve (Mehler et al., 2014). It is important to consider the amount of time required to truly understand the technology being provided in the vehicle before turning drivers loose on public roadways with these advanced features.

Human Centric Training Elements. One element that is notably lacking from current training practices for driving automation is a human centered component. Drivers need to understand what their role is in the human-machine relationship and what effect automation may have on their behavior.

Operator Responsibility. As mentioned previously, the introduction of automation presents new tasks that the human operator is responsible for performing. Many have argued that the marketing name of a system may encourage the misalignment of driver expectations. Abraham, Seppelt, Mehler, and Reimer (2017) found that brand names do influence consumer perceptions of technologies, however, these naming schemes do not offer adequate information to appropriately inform the driver of their role while using driving automation. The results from the research presented in **Chapters 2, 3, and 4** pertaining to driver eye glance behavior indicate that drivers need to be educated about their responsibility in completing the OEDR subtask. When operators believe system capabilities exceed the actual capabilities, system misuse and complacency may be observed (Parasuraman & Riley, 1997). Drivers must be sufficiently educated regarding their responsibility when using driving automation systems.

Human Factors – Human interaction with automation. The results of this dissertation support the findings of other research about operator behavioral change with the introduction and use of automation. Drivers in this research demonstrated a tendency to reduce their monitoring of the roadway to varying degrees while using the driving automation systems, the same has been found in other studies (Llaneras et al., 2013; Mosier et al., 1998; Parasuraman et al., 2008). These changes in performance may stem from lack of relevant experience with the given task demands (Stanton & Young, 2005), vigilance decrements (Endsley & Kiris, 1995; Louw et al., 2017; Louw & Merat, 2017; Merat et al., 2019; Strand et al., 2014) or complacency with the automated systems (Bahner et al., 2008; Manzey et al., 2006; Singh et al., 1993b, 1993a).

Vigilance. It is taught that drivers must pay attention to the road and look for hazards when they are operating a vehicle without any assistance systems active. However, emphasis is lost on this responsibility when driving automation systems are active. It is the responsibility of the

human operator to oversee and coordinate performance when driving automation systems are in use (Bradshaw, Hoffman, Woods, & Johnson, 2013), which is a vigilance task. Mackworth (1948) showed how an individual's ability to detect signals changes over time. Initially, the rate of signal detections were good (approximately 85%), however, it declined sharply within the first 30 minutes of the session (to approximately 75%), then showed a more gradual decline for the remainder of the two-hour observation (to a value of approximately 70%). The results from **Chapter 3** indicated that drivers spent more time looking away from the road scene while automation was active and they were more likely to browse on their cellphone. Driver's ability to respond to hazards is compromised in the absence of full attention (Merat et al., 2012), therefore it is imperative that drivers pay appropriate attention to the road scene.

In aviation, it was noted by Casner and Schooler (2015) that individuals performing monitoring tasks outside of the laboratory may experience high rates of monitoring lapses for three reasons which have stark parallels to the driving environment. First they are required to use a continuous vigilance approach – much like operators of driving automation systems. Second, pilots work in a dynamic environment that cannot fully be controlled. Finally, as the pilots are human they experience the irresistible, albeit natural urge to let one's thoughts drift. According to Casner and Schooler, monitoring lapses are inevitable and while it is unlikely that we will eliminate the problems associated with long uninterrupted watches, the management of internal and external distractions may help mitigate these issues. These lessons should be considered when developing training protocols for driving automation; we cannot control the driving environment but we can attempt to minimize distractions in the vehicle and inform drivers of the possibility of mind wandering, drowsiness, and potential consequences of monitoring lapses.

Automation Bias and Complacency. Drivers should be educated about automation bias and complacency – including their tendency to overestimate their ability to pay attention to or respond to unexpected events (Casner & Hutchins, 2019; Onnasch et al., 2014). As mentioned previously, operators sometimes rely on automation as a heuristic replacement for attentive information seeking and processing (Mosier, Skitka, Burdick, & Heers, 1996) and operators had difficulty troubleshooting system performance.

Muhrer & Vollrath (2011) found that drivers' maintained a larger time-gap while engaged in visual distractions in a simulated conventional (un-assisted) car following scenario, likely to compensate for their impaired perception of the road scene. When driving automation systems are active, however, drivers' have relinquished the control of longitudinal motion to the automation. The results in **Chapter 4** demonstrated that drivers' time-gap decreased while drivers' were using the driving automation systems, and while there was no increase in the likelihood of secondary task engagement in that study, we consistently found that drivers looked away from the road longer while driving automation was active compared to when it was available (**Chapter 2, 3, and 4**). Furthermore, the research presented in **Chapter 3** indicated that drivers are more likely to engage in high-risk (visual-manual) secondary tasks while using their driving automation systems.

Victor et al. (2018) found that, while system-based reminders influenced driver's eyes on-road and hands on-wheel behavior, prompts or explicit instructions regarding system limitations and supervision responsibilities were not able to prevent 28% of participants from colliding with an obstacle in the roadway despite seeing the hazard. This may suggest that participants were overly reliant on the vehicle system due to incorrect expectations of system capabilities. By training drivers to have appropriate expectations and informing them of the possibility of bias and reliance during training, we are providing drivers of realistic expectations of the automation's role

in the completion of the driving task and informing them of their role and deficiencies in the same task.

How training needs to change over time

A decision-maker relies upon knowledge that is readily available rather than searching for new information. Consequently, individuals will have a tendency to weigh judgements towards more recent information. When a user has strong availability bias, judgements are fueled by the ease with which examples come to mind. This can pose major barriers to the implementation and safe widespread use of vehicle automation. As drivers gain experience using the system and continue to construct and refine their mental models, their needs will change. The growth of trust will depend on their ability to estimate the automation's behaviors (Lee & Moray, 1992; Muir, 1987). Trust stands between beliefs about the characteristics of the automation and the intention to rely on the automation. Therefore, it is important to provide users with training over time to remind them of their role in using the automated systems and the capabilities and limitations of the system. Additionally, providing users with information about their performance of the OEDR subtask and how their driving performance changes over time would be beneficial. The methods by which we provide users with opportunities to practice, understanding of the capabilities and limitations of the systems, and their performance over time are described in the following sections.

Opportunities to practice and apply skills

Skills in complex tasks, including those with large social components, are usually taught best by a combination of training procedures involving both whole tasks and components or part-tasks (Anderson, Reder, & Simon, 1996). Using situations that are relevant to the learner provides an opportunity for learners to engage in reflective thinking (Federal Aviation Administration, 2009; Shor, 1996). However, incorporating a restrictive definition of authenticity in training design

will result in learning environments that are authentic in a narrow context, thereby reducing the variability of skills and strategies acquired by the learner. Training should teach trainees to be innovative, creative, and adaptable so that they can deal with the demands of domains that are complex and ill-structured (Federation of American Scientists, 2005; Gee, 2003; Prensky, 2001).The inclusion of related cases in training can scaffold the learner's memory by providing representations of experiences that learners have not had (Jonassen, 1999), especially in ill-defined domains and for non-recurrent skills (Merrill, 2002; Schwartz, Lin, Brophy, & Bransford, 1999; van Merriënboer & Kirschner, 2017).

Embedded Training

Embedded training is described as a training program built into systems so operational equipment can be switched over to a "training mode" during periods when it is not needed for operational use (Sanders & McCormick, 1993, p. 745). Strategies mentioned in the previous section can be incorporated into this type of training to facilitate skill and knowledge acquisition at an appropriate level and enhance engagement by being appropriately difficult. The training needs of users will change from their first exposure to the vehicle systems to their one hundredth exposure (Gagné, 1965). In their initial exposure, operators will need to be familiarized with the system interface, purpose, methods of activation and deactivation, and basic system signals. This could be done using the vehicle interface and multimedia methods so that auditory alerts are consistent, as are the placement, size, shape, and color of icons pertinent to the system. However, with increased exposure to the system, driver's perceived familiarity with the system will increase (demonstrated in **Chapter 2**). This motivates the need for feedback, monitoring, and understanding when to end training. These training tools are important omissions from current consumer education practices.

Feedback and monitoring. "Practice makes perfect" is a common saying; however, practice is of very little value when the results of an action are unknown or incorrect. Knowledge of results, or extrinsic feedback, is an important tool in the growth and development of learners because it provides an indication of discrepancy between actual and desired behavior (Patrick, 1992, p. 326). Learning is promoted when learners are guided in their problem solving by appropriate feedback mechanisms, which include error detection and correction (Gagné, 1965; Merrill, 2002). Feedback comes not only in the form of coaching, but also from the visual, auditory, and proprioceptive information associated with normal (correct) task execution. Consequently, Annett (1961) specified the difference between intrinsic feedback, which pertains to information concerning normal (non-training) task performance, and extrinsic feedback, which refers to additional knowledge supplied during training and not available during typical task performance.

Extrinsic feedback can be provided in real-time during task performance or at some point after task completion (post-hoc). Real-time and post-hoc feedback for novice driver training has been shown to improve teen driving safety as well as reduce the frequency of risky driving behaviors (Klauer et al., 2017; Peek-Asa, Hamann, Reyes, & McGehee, 2016). Research has also found that continuous feedback promotes more accurate mental models of system performance than discrete feedback and is believed to promote more accurate mental models of system limits. Accurate mental models are expected to prompt proactive driver responses, initiated before driving automation systems exceed their limit whereas inaccurate mental models are expected to result in reactive driver responses, initiated after driving automation systems have exceeded their limits (Seppelt, 2009; Seppelt & Lee, 2007).

Personalized feedback coupled with active practice has also been shown to be superior to

passive learning methods with no feedback when assessing older driver's scanning behaviors at intersections (Romoser, Pollatsek, Fisher, & Williams, 2013). Using real-time feedback for adults to assist them in learning/understanding driving automation systems could be a useful technique; however, additional research is needed on this topic. If it can be determined that driver performance deficiencies are attributable to a lack of skill or knowledge, then an immediate training intervention after the first occurrence of the undesired behavior in-situ may help to correct the behavior. However, if undesirable safety-related performance deficiencies cannot be attributed to a lack of skill or knowledge, then the solution does not lie in training, but in the application of salient differential consequences (Boldovici, 1992; Mager & Pipe, 1970). One example is the Tesla Autosteer system deactivation for non-compliance with hands on wheel warnings (Tesla Inc., 2018).

Termination of Training Program. Giving learners complete control over when they may terminate learning invites overconfidence that a skill has been fully mastered. If the learner's metric for self-evaluation is heavily dominated by error-free performance, a highly salient measure, they may terminate their training too soon. Personal, unguided reflection on performance and understanding is a task people rarely perform well (Kruger & Dunning, 1999; Regehr & Eva, 2006). Fitts (1962) advocated that training should be continued beyond a minimum performance criterion and that skills acquired during training should be sufficiently versatile to withstand the change from a structured training situation to the less predictable application in the real world. Consequently, the criterion for trainee performance must be carefully defined and termination of training by trainee-selection is not recommended.

According to Spitzer (1984), there is an unwritten law that training programs last a certain number of days, with lectures of a certain duration and breaks at specified times. This notion

contributes to the erroneous idea that learning is a time-bound event that only occurs in certain defined time periods. Skills acquired during periods of training need to be sufficiently versatile to withstand the transition from the organized training context to the less predictable real world domain. With merely "acceptable" performance, the fragile skill acquisition process will be easily disrupted unless further training is provided.

The importance of training drivers is critical to the successful deployment of driver support features from low to high levels of automation. As discussed in this chapter, the high variability of drivers on our roadways and the competing strengths and limitations of current driving automation systems present challenges that transportation safety researchers must address. Given these challenges, there are several recommendations listed below.

Recommendations

1. Training objectives and materials should change as the driving task and the human operator's role continues to evolve and change.
2. Training the human user should be considered as a key focus in system design – training programs should be intentionally evaluated.
3. A well-designed driver monitoring system and providing driver feedback are very important. These systems will become imperative as the driving task changes.
4. Effective training guidelines and procedures need to be developed.
5. Key stakeholders, specifically legislators must be educated about driving automation systems so that laws pertaining to driving automation can be derived from science and fact. This will become particularly relevant when it becomes

time to review and adapt existing rules regarding vehicle operation and driver training.

Training objectives and materials should be dynamic and flexible as driving automation systems continue to develop, new data become available, and the driving task continues to change. For example, new training requirements could arise from a driver's increased exposure (and familiarity) with particular systems or software updates.

Second, considerations for the training of system users should be included as a key point in the design cycle of these new systems. Training programs should be subjected to the proper evaluation and assessment to ensure that learning outcomes are achieved and no unintended consequences are introduced by the program.

Third, in-vehicle driver monitoring systems may be an important option to consider for driving automation system training and real time feedback. Campbell et al. (2018) discussed the use of driver monitoring systems to avoid out-of-the-loop problems. Salinger (2018) discussed a driver monitoring system which presented multimodal signals to capture drivers' attention and return focus back to the control or monitoring loop. The National Transportation Safety Board (2017, 2020) has recommended implementing driver monitoring systems that monitor the driver's attention to the roadway rather than their inputs to other vehicle controls to provide an adequate safeguard against driver inattention and complacency.

Fourth, traffic safety professionals need to develop effective training guidelines and procedures for driving automation systems. Currently, the California Department of Motor Vehicles requires specific training programs for drivers who test highly automated systems (SAE Level 3 and above) on public roads, which includes: familiarization with the automated driving system technology; basic technical training regarding the system concept, capabilities, and

limitations; ride-along demonstrations by an experienced test driver; and subsequent behind-the-wheel training (Nowakowski, Shladover, Chan, & Tan, 2014). Perhaps another worthwhile endeavor in the near term would be to add some measure of advanced vehicle system components to future iterations of the basic knowledge test for the standard licensing requirement, similar to what was implemented in at least twenty states and the District of Columbia for distracted driving as of 2013 (Governors Highway Safety Association, 2013).

Finally, legislative action amending statutory and regulatory definitions of applicable terms (e.g. driver, vehicle, etc.) as well as reviewing and adapting existing rules regarding vehicle operation may be a persistent challenge until policymakers are well versed in the subject matter. Educating all entities on the need for acceptance and implementation of these universal terms and definitions will be an implementation challenge (American Association of Motor Vehicle Administrators, 2018). This is one reason why communication between researchers and legislators must be clear and concise so that, in the event legislation is required, it is based on science and not on other implicit or explicit biases. Furthermore, all key stakeholders are encouraged to communicate with one another on the most effective ways to train novice and experienced drivers on driving automation systems. Educational materials that are developed should be proven effective and able to be understood by the general motoring public.

Chapter 6. Conclusions

Summary of Findings

A primary focus of this dissertation is understanding drivers' completion of the Object Event Detection Response (OEDR) subtask while assisted by driving automation systems by assessing their observable behaviors. A series of studies were completed which assessed 1) how drivers training and experience influences knowledge, behavior, and attitudes toward driving automation systems; 2) a yearlong observational study of driver behavior with driving assistance systems in their personal vehicles; and 3) examining driving behavioral change with unfamiliar driving automation systems over time.

The results of this dissertation indicate that although driving automation systems are becoming more common in the vehicle fleet, consumers are not being appropriately educated on how to use them. While rudimentary tasks such as system activation and deactivation are sufficiently addressed in the operator's manual, interactions with sales staff, and through practice (Abraham, Reimer, et al., 2017), insufficient emphasis is being placed on the driver's responsibility to monitor the road scene and their role in responding to hazards. Drivers' expectations of the capabilities of driving automation systems vary widely and are largely influenced by naming scheme, marketing, and previous experience (Abraham, Seppelt, et al., 2017; Seppelt et al., 2018). While it is important to respect the vehicle manufacturer's desire for individuality, it is even more important to appropriately inform the consumer about their responsibility as stewards of the road and the limitations of the technologies in their vehicles.

The research presented in **Chapter 2** indicated that the mode of training elicited limited knowledge, performance, and attitude differences. This indicates that beyond the mode of presentation, other issues associated with consumer education include nature of the material being

presented as well as the *consolidation* of this information. Participants spent an average of 17.85 minutes (SD=3.83 minutes) reviewing the training content before driving the test vehicle. The primary contributor to attitude and performance differences was exposure to the driving automation systems, for better or for worse. After gaining experience using the system, participants indicated that they were more familiar with the driving automation systems, however, they were not monitoring the forward roadway with the same perlustration as they were at the onset of the study. This provides a basis for the hypothesis that, with increased exposure in the absence of adverse events comes decreased environmental monitoring.

The research presented in **Chapter 3** focused on driver use and performance of the OEDR sub-task. This was motivated by the changes in environmental monitoring and increased perceived familiarity demonstrated in **Chapter 2**. Drivers in **Chapter 3** were using their own vehicles on public roadways, which introduces many new factors that were not accounted for in the research presented in **Chapter 2**. The results of the research presented in **Chapter 3** showed that drivers used their driving automation systems in anticipated environments; on longer trips, higher speed roadways, and roads that are controlled access. However, it was also found that drivers tended to look away from the roadway longer when driving automation systems were active compared to when they were available but not active. Additionally, driver engagement in high-risk secondary tasks such as cellphone browsing were noted to be higher for drivers using driving automation versus when the systems were available but not active. This indicates that on public roads drivers in their personal vehicles are willing to perform secondary tasks more often while systems are active compared to when they are inactive but available. Therefore, drivers are less able to complete the OEDR sub-task sufficiently because they are not looking at the road scene as much. It is important to attempt to identify when this behavioral shift occurs, which motivated the

research presented in **Chapter 4**.

The research in **Chapter 4** assessed driver behavioral adaptation with the driving automation systems. The results of this study demonstrate longitudinal control tasks such as time-gap change with increased exposure to driving automation systems. While there were no statistically significant differences were observed for eye glance measures over time, a possible trend emerged, in which the duration of off road glances increased with greater L2 exposure. The discrepancies between the eye glance results presented in **Chapter 3** and **Chapter 4** offer an interesting perspective on driver behavioral adaptation. In particular, they indicate that perhaps a longer observation period than what was attained from the data presented in **Chapter 4** may be required to observe a significant change in driver glance behavior as a function of L2 exposure when compared to unassisted exposure.

Challenges and Conclusions

The true challenges that accompany the mass deployment of driving automation systems lie in the modification of the driving task. We are changing the roles and responsibilities of driving from a process where the system supports the human driver to a process where the driver supports the system. Given this change in the driving task, engineers will not be able to design their way to safety by the traditional means of usability and clear operating instructions. While having intuitive and understandable HMI is crucial to the success of driving automation systems, we must also work to ensure that effective training is made available for all users. Stakeholders from all parts of the transportation system need to work together on this issue for driving automation to deliver on it promises and ensure consumer awareness of the capabilities and limitations of these systems.

The idea of re-training and re-certification is not uncommon in aviation and commercial surface transportation applications (e.g., trucking), however, in passenger vehicles, once you

receive your license there is no re-check on skills and knowledge. Intermittent examination, be-it informal rechecks on driving automation system capabilities and limitations, as well as human factors issues such as automation bias and complacency, could be beneficial. The results of this and future research could be used by vehicle manufacturers, system designers, and automotive dealerships to design training materials and technologies with the goal of better informing the motoring public of system capabilities and operator responsibilities.

Practical Implications

The findings of this dissertation research contribute to the larger body of work by identifying shortcomings of driver performance in the driving task while aided by driving automation systems through multiple methods, including test track research and naturalistic data collection. This research has indicated that training drivers to pay attention to the roadway while using driving automation is a critical component of the driving task but is often under emphasized in current training materials. It is important to develop and implement training guidelines (such as those presented in **Chapter 5**) that emphasize the drivers' role in safe vehicle handling when driving automation is active. Driver training will remain crucial to the successful deployment of driver support features across all levels of driving automation. The high variability of drivers' willingness to trust automation and their motivations for using these systems, coupled with the strengths and limitations of current driving automation features, present a multitude of challenges that transportation safety researchers will have to address for years to come.

Future Research

Research human-automation interaction in surface transportation have identified key topics for initial training at the time of vehicle purchase and for early exposure to automated systems. However, there is a limited body of work that exists on driver behavior with vehicle automation over time and what does exist does not assess driver behavior using naturalistic methods. Many studies involve short, controlled, experimental sessions (Beggiato, Pereira, Petzoldt, & Krems, 2015; Pereira, Beggiato, & Petzoldt, 2015; Piccinini, 2014; C. M. Rudin-Brown & Parker, 2004; Vollrath, Schleicher, & Gelau, 2011). The key limitation of prior work that is addressed by this dissertation is the assessment of how drivers behave while using driving automation over time during their day to day driving whether in their personal vehicles or a leased vehicle.

There is no shortage of future research in the area of behavioral adaptation with driving automation systems. Any time humans are given a new technology they inevitably find a way to exploit it to suit their own needs for better or for worse. A limited sample of the possibilities for future research in driver behavior with level 2 systems includes: 1) the development and evaluation of future training and consumer education programs for driving automation systems; 2) longitudinal studies of driver performance and attitudes toward driving automation systems with deliberate sampling of familiarity, trust, and other important constructs; and 3) an assessment of the secondary task type and the amount of time spent completing the task while driving automation systems active compared to when they are inactive. Research in the area of driver training and behavior with automation should continue for as long as the human is expected to have any role in the driving task in order to support accurate mental model development and trust.

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Appendix A. Driver Training for Automated Vehicle Technology Training Topics

Tesla Content Header	Sub-Header	Description
Driver Assistance Features	About Driver Assistance Features	Lists types of features
	Driver Assistance Components	Lists components used to actively monitor the roadway environment
	Limitations	Factors that can influence the performance of driver assistance components.
Traffic-Aware Cruise Control	Overview	The functional purpose of traffic aware cruise control and the operational design domain.
	Operating TACC	Instructions for operation (activation
	Adjust Following Distance	Instructions for adjusting the following distance
	Changing Set Speed	Instructions for adjusting the set speed
	Canceling/Resuming	Instructions for canceling/resuming adaptive cruise control
	Summary of Cruise Indicators	Summary of icons on the instrument panel
	Situations where TACC may not be available	Situations where Traffic-Aware Cruise Control may not operate as intended.
	Warnings and Limitations	
Autosteer	Overview	The functional purpose of Autosteer
	Operating Autosteer	How to activate Autosteer and change settings
	Restricted Speed	Functional limitation based on road environment
	Hold the Steering Wheel	Warning/alert
	Take Over Immediately	Warning/alert
	Canceling Autosteer	How to cancel Autosteer
	Warnings and Limitations	Situations where Autosteer may not operate as intended.

Excluded Content

Specific automated features were excluded from the training material due to system or test track constraints. The sections that were removed are listed below with the justification for their removal:

Cruising at the speed limit (Autosteer): The Smart Road is a controlled access facility and therefore does not have a uniformly applied speed limit. After the 2016 fatal Tesla crash in Williston, FL software updates in version 8.1 limit the speed top of Autosteer to 45 mph on roads where the speed limit cannot be detected.

Overtake acceleration (Autosteer): Participants will not be overtaking other vehicles in this study. This feature is outside of the performance specifications of a standard adaptive cruise control design and will not be covered in either training protocol.

Additional automated features available as part of the Autopilot 8.1 software package such as automatic lane change were disabled and not covered during the training protocol to prevent unintentional lane changes during the experimental session.

Automatic emergency braking and forward collision warning were not covered during the training session, however, the research team left these systems active as a safety measure.

Appendix B. Chapter 2: Driver Training for Automated Vehicle Technology Informed Consent

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY
Informed Consent for Participants of Investigative Projects

Title of Project: UTC Training [Driver Training for Automated Vehicle Technology]

Investigators: Charlie Klauer, Alexandria Noble, Gayatri Ankem

I. THE PURPOSE OF THIS RESEARCH PROJECT

There are few types of training available to help people understand the technology inside their car. Automated vehicles are becoming widely available and it is important that drivers can use them safely and appropriately. This project will look at how training effects user knowledge and control of automated systems.

We are asking you to help us with this study. If you choose to participate, you will be asked to complete a training module and drive an automated vehicle on our test track. The results of this study will be used to develop guidelines for future training.

II. PROCEDURES

During the course of this experiment, you will be asked to perform the following tasks:

1) Read this Informed Consent Form and sign it if you agree to participate.
2) Complete a W-9 form.
3) Show your valid driver's license.
4) Complete a vision and hearing test.
5) Complete questionnaires throughout the study.
6) Complete an in-vehicle training module on automated vehicle technology.
7) After completion of the training modules, we will proceed to the test track. The experimenter will be in the car with you the entire time you are on the test track.
8) While the car is parked on the test track, the experimenter will show you how to perform different in-vehicle tasks (e.g., change the radio station, send a text using a VTTI phone, locate an item in the vehicle).
9) Then you will be asked to drive 8 laps on the road while performing the different tasks as instructed by the experimenter.
10) Then the researcher will ask you some questions about your experience.
11) The maximum speed limit will be 45 miles per hour.
12) Other vehicles driven by VTTI researchers will be on the Smart Road to simulate real traffic conditions.
13) You will be asked not to wear sunglasses or eye glasses with photochromic lenses unless absolutely necessary. If you are suffering from glare and cannot see the roadway, please let the experimenter know.
14) While you are in the vehicle, digital video will be recorded, including your face. Continuous audio will also be recorded.

It is important for you to understand that we are not evaluating you or your performance in any way. You are helping us to evaluate the effectiveness of a new training module for automated

vehicle systems. The opinions you have will help us determine appropriate guidelines for new training protocols. The information and feedback that you provide is very important to this project. Today's total experiment time last up to 2 and a half hours.

III. RISKS

There are risks or discomforts which you may experience while volunteering for this research. They may include the following:

1. The risk of an accident normally present while driving an unfamiliar vehicle on a closed-course test track with medium traffic, during dry/clear weather conditions at maximum speeds of 45 mph.
2. Possible fatigue due to the length of the experiment. However, you may take breaks if necessary.
3. The additional risk of an accident that might occur while performing secondary tasks while driving.

While the risk of participation in this study is considered to be no more than that encountered in everyday driving, if you are pregnant you should talk to your physician and discuss this information sheet with them before making a decision about participation.

Please be aware that events such as equipment failure, changes in the test track, stray or wild animals entering the road, and weather changes may require you to respond accordingly. If at any point in the session the experimenter believes that continuing the session would endanger you or the equipment, he/she will stop the testing.

In the event of an accident or injury in an automobile owned or leased by Virginia Tech, the automobile liability coverage for property damage and personal injury is provided. The total policy amount per occurrence is $2,000,000. This coverage (unless the other party was at fault, which would mean all expense would go to the insurer of the other party's vehicle) would apply in case of an accident for all volunteers and would cover medical expenses up to the policy limit. For example, if you were injured in an automobile owned or leased by Virginia Tech, the cost of transportation to the hospital emergency room would be covered by this policy.

Participants in a study are considered volunteers, regardless of whether they receive compensation for their participation; under Commonwealth of Virginia law, worker's compensation does not apply to volunteers; therefore, if not in the automobile, the participants are responsible for their own medical insurance for bodily injury. Appropriate health insurance is strongly recommended to cover these types of expenses. For example, if you were injured outside of the automobile owned or leased by Virginia Tech, the cost of transportation to the hospital emergency room would be covered by your insurance.

The following precautions will be taken to ensure minimal risk to you:

1. An experimenter will be with you at all times to monitor your driving and will ask you to stop if he/she feels the risks are too great to continue.
2. You may take breaks or decide not to participate at any time.
3. You will be required to maintain a specific speed for each given task. The experimenter will inform you of the speed before each task is performed. The maximum speed limit on

the road for this study will be 45 miles per hour. The testing will take place on a closed, controlled test track.

4. The experimenter will be present while you are driving. As long as you are driving the research vehicle, it remains your responsibility to drive in a safe and legal manner.
5. You will be required to wear your lap and shoulder belt restraint system while in the car. The vehicle is equipped with a driver's side and passenger's side airbag supplemental restraint system, fire extinguisher, and first aid kit. The experimenter will also have a cell phone.
6. All data collection equipment is mounted such that, to the greatest extent possible, it does not pose a hazard to you in any foreseeable case.
7. The experimenter will end the experiment if inclement weather occurs. This includes any weather that results in the use of the windshield wipers, wet or icy road surfaces, and reduced visibility due to fog.
8. The other drivers on the road are trained VTTI experimenters.
9. All secondary tasks will occur on the straight section of the test track and will not take place on bridges.
10. Driving is the primary task and you should only perform secondary tasks when it is safe to do so.
11. You do not have any medical condition that would put you at a greater risk, including but not restricted to history of neck/spine injury, epilepsy, balance disorders, lingering effects of head injuries and stroke, and advanced osteoporosis.
12. In the event of a medical emergency, or at your request, VTTI staff will arrange medical transportation to a nearby hospital emergency room. You may elect to undergo examination by medical personnel in the emergency room.

IV. BENEFITS

While there are no direct benefits to you from this research, you may find the experiment interesting. No promise or guarantee of benefits is made to encourage you to participate. Participation in this study will contribute to the improvement of future training practices for autonomous vehicle systems.

V. EXTENT OF ANONYMITY AND CONFIDENTIALITY

The data gathered in this experiment will be treated with confidentiality. Shortly after participation, your name will be separated from your data. A coding scheme will be employed to identify the data by participant number only (e.g., Participant No. 1).

It is possible the Virginia Tech Institutional Review Board (IRB) may view this study's collected data for auditing purposes. The IRB is responsible for the oversight of the protection of human subjects involved in research.

Data collected by this project will be uploaded and archived in a Safe-D UTC data repository maintained by Virginia Tech Transportation Institute. A dataset may also be made publicly available. The public dataset will be de-identified and will not contain any information that might lead to the identification of an individual participant.

Data collected during this research project, including video and audio data, will be made available to external researchers. Data availability will be governed by a data sharing agreement. At no time will the researchers release data identifiable to you or the digital video of your image to anyone that has not agreed to abide by a data sharing agreement including IRB approval. The data collected will be retained indefinitely. Also, video and audio data that may identify you may be shown by VTTI staff, but not released, for research or reporting purposes such as presentations.

VI. COMPENSATION

You will be compensated at the rate of $30 per hour, rounded to the nearest ½ hour. If the session ends early for any reason, you will be compensated for the amount of time you participated. Compensation for full participation will be $75. All compensation will be issued using a pre-loaded MasterCard. Please allow up to 1 full business day for activation of the card. Once activated, this card cannot be used past its expiration date. The issuing bank will begin deducting a monthly service fee of $4.50 after three months of inactivity. Expected participation time will be for one visit, lasting approximately two and a half hours.

If compensation is in excess of $600.00 dollars in any one calendar year, then by law, Virginia Tech is required to file Form 1099 with the IRS. For any amount less than $600.00, it is up to you as the participant to report any additional income as Virginia Tech will not file Form 1099 with the IRS.

Also, you will be asked to provide researchers with your social security number or Virginia Tech I.D. number for the purposes of being compensated for your participation. For tax recording purposes, the fiscal and accounting services office at Virginia Tech (also known as the Controller's Office) requires that all participants provide their social security number or Virginia Tech I.D. number to receive compensation for participation in our studies.

VII. FREEDOM TO WITHDRAW

As a participant in this research, you are free to withdraw at any time without penalty. If you choose to withdraw, you will be compensated for the portion of time of the study for which you participated. Furthermore, you are free not to answer any question or respond to experimental situations without penalty. If you choose to withdraw during the study session, please inform the experimenter of this decision and he/she will drive you back to the building.

VIII. APPROVAL OF RESEARCH

This research project has been approved, as required, by the Institutional Review Board for Research Involving Human Subjects at Virginia Polytechnic Institute and State University. This form is valid for the period listed at the bottom of the page.

IX. PARTICIPANT'S RESPONSIBILITIES

If you voluntarily agree to participate in this study, you will have the following responsibilities:

1. To follow the experimental procedures as well as you can.
2. To inform the experimenter if you have difficulties of any type.
3. To wear your seat belt while operating the vehicle.
4. To abstain from any substances that will impair your ability to drive.
5. To adhere to the 45 mph speed limit on the test track, and maintain safe operation of the vehicle at all times.
6. To treat the driving task as the primary task and perform other tasks only when it is safe to do so.

Check all that apply:

- ☐ I am not under the influence of any substances or taking any medications that may impair my ability to participate safely in this experiment.
- ☐ I am in good health and not aware of any health conditions that would increase my risk including, but not limited to lingering effects of a heart condition.
- ☐ I have informed the experimenter of any concerns/questions I have about this study.
- ☐ I understand that digital video including my image will be collected as part of this experiment.

- ☐ If I am pregnant, I acknowledge that I have either discussed my participation with my physician, or that I accept any additional risks due to pregnancy.

XI. PARTICIPANT'S PERMISSION

I have read and understand the Informed Consent and conditions of this project. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent for participation in this project. **If I participate, I may withdraw at any time without penalty. I agree to abide by the rules of this project.**

_____	_____	_____
Participant's name (Print)	Signature	Date
_____	_____	_____
Researcher's name (Print)	Signature	Date

Should I have any questions about this research or its conduct, I may contact:

Dr. Charlie Klauer	540-231-1564	cklauer@vtti.vt.edu
Alexandria Noble		anoble@vtti.vt.edu

Should you have any questions or concerns about the study's conduct or your rights as a research subject, or need to report a research-related injury or event, you may contact:
Virginia Tech Institutional Review Board for the Protection of Human Subjects
Telephone: (540) 231-3732; Email: irb@vt.edu

Appendix C. Driver Training for Automated Vehicle Technology Trust Questionnaire

1. I would rely on vehicle automation to function properly while I am doing something else.

1	**2**	**3**	**4**	**5**	**6**	**7**
Strongly Disagree			No Opinion			Strongly Agree

2. I would rely on vehicle automation to provide alerts when needed.

1	**2**	**3**	**4**	**5**	**6**	**7**
Strongly Disagree			No Opinion			Strongly Agree

3. Vehicle automation gives false alerts.

1	**2**	**3**	**4**	**5**	**6**	**7**
Strongly Disagree			No Opinion			Strongly Agree

4. Vehicle automations is dependable.

1	**2**	**3**	**4**	**5**	**6**	**7**
Strongly Disagree			No Opinion			Strongly Agree

5. I am familiar with vehicle automation.

1	**2**	**3**	**4**	**5**	**6**	**7**
Strongly Disagree			No Opinion			Strongly Agree

6. I trust vehicle automation.

1	**2**	**3**	**4**	**5**	**6**	**7**
Strongly Disagree			No Opinion			Strongly Agree

Administered: Pre-Training, Post-Training, and Post-Drive

Appendix D. Chapter 2: Knowledge Questionnaire

1. Please select all roadway environments where it would be appropriate to use Adaptive Cruise Control (ACC, TACC).

   - ☐ Divided highways and roadways
   - ☐ Carpool/HOV Lanes
   - ☐ Roundabouts and traffic circles
   - ☐ Toll roads
   - ☐ Gravel Roads
   - ☐ Parking lots
   - ☐ Local roads and streets
   - ☐ Residential streets

2. Please select all situations where it would be appropriate to use Lane Keeping Assist (LKA, Autosteer).

   - ☐ Divided highways and roadways
   - ☐ Carpool/HOV Lanes
   - ☐ Roundabouts and traffic circles
   - ☐ Toll roads
   - ☐ Gravel Roads
   - ☐ Parking lots
   - ☐ Local roads and streets
   - ☐ Residential streets

Please select all situations from the following where Adaptive Cruise Control (ACC, TACC) may not work as expected.

- ☐ Extremely hot or cold temperatures
- ☐ Clear sunny days
- ☐ Dusk and dawn
- ☐ Heavy rain or snow
- ☐ Poor tire traction
- ☐ Sensors are obstructed
- ☐ Windy road
- ☐ Straight roads
- ☐ Roads with poor lane markings
- ☐ Roads with no lane markings
- ☐ Roads with clearly visible lane markings
- ☐ Work Zones
- ☐ Toll plazas

3. Please select all situations from the following where Lane Keep Assist (LKA, Autosteer) may not work as expected.

- ☐ Extremely hot or cold temperatures
- ☐ Clear sunny days
- ☐ Dusk and dawn
- ☐ Heavy rain or snow
- ☐ Poor tire traction
- ☐ Sensors are obstructed
- ☐ Windy road
- ☐ Straight roads
- ☐ Roads with poor lane markings
- ☐ Roads with no lane markings
- ☐ Roads with clearly visible lane markings
- ☐ Work Zones
- ☐ Toll plazas

4. What sensor(s) is/are used by Adaptive Cruise Control (ACC, TACC)? Select all that apply.

- ☐ Forward Looking Camera
- ☐ Forward Looking Radar
- ☐ Ultra Sonic Sensors
- ☐ GPS
- ☐ Rearview camera

5. What sensor(s) is/are used by Lane Keeping Assist (LKA, Autosteer)? Select all that apply.

- ☐ Forward Looking Camera
- ☐ Forward Looking Radar
- ☐ Ultra Sonic Sensors
- ☐ GPS
- ☐ Rearview camera

Administered: Post-Training and Post-Drive

Appendix E. Attitudes toward Training Regression

Research Question	Source	DF	SS	MS	F Value	Pr > F
Q60. Objectives clearly defined.	**Age Group**	1	0.225	0.225	0.43	0.5169
	Training	1	0.025	0.025	0.05	0.8285
	Age Group × Training	1	0.625	0.625	1.19	0.2825
	Error	*36*	*18.9*	*0.53*		
Q61. Participation and interaction were encouraged.	**Age Group**	1	1.225	1.225	1.72	0.1985
	Training	1	0.225	0.225	0.32	0.578
	Age Group × Training	1	0.625	0.625	0.88	0.3557
	Error	*36*	*25.7*	*0.71*		
Q62. Topics covered were relevant to me.	**Age Group**	1	1.225	1.225	1.35	0.2532
	Training	1	0.025	0.025	0.03	0.8692
	Age Group × Training	1	2.025	2.025	2.23	0.1441
	Error	*36*	*32.7*	*0.91*		
Q63. Content was well organized and easy to follow.	**Age Group**	1	0.625	0.625	0.63	0.4337
	Training	1	0.025	0.025	0.03	0.8751
	Age Group × Training	1	0.225	0.225	0.23	0.6377
	Error	*36*	*35.9*	*1.00*		
Q65. The time allotted for training was sufficient.	**Age Group**	1	0.225	0.225	0.15	0.699
	Training	1	1.225	1.225	0.83	0.3691
	Age Group × Training	1	0.025	0.025	0.02	0.8973
	Error	*36*	*53.3*	*1.48*		
Q64 - The training experience was useful in operating the vehicle automation.	**Age Group**	1	0.030	0.030	0.04	0.851
	Training	1	0.203	0.203	0.24	0.6268
	Age Group × Training	1	0.019	0.019	0.02	0.8808
	Error	*35*	*29.49*	*0.84*		
Q91 - Do you feel the training adequately prepared you for operating the vehicle?	**Age Group**	1	1.225	1.225	1.15	0.2904
	Training	1	1.225	1.225	1.15	0.2904
	Age Group × Training	1	1.225	1.225	1.15	0.2904
	Error	*36*	*38.30*	*1.06*		

Appendix F. Trust Scale IRRs

Trust Scale IRR - Pre Training

The CORR Procedure

Simple Statistics							
Variable	**N**	**Mean**	**Std Dev**	**Sum**	**Min.**	**Max.**	**Label**
Q1	40	3.28	1.65	131.00	1.00	7.00	Q1
Q2	40	4.80	1.74	192.00	1.00	7.00	Q2
Q3	40	3.58	1.01	143.00	1.00	6.00	Q3
Q4	40	4.58	1.01	183.00	3.00	6.00	Q4
Q5	40	3.43	1.58	137.00	1.00	6.00	Q5
Q6	40	4.10	1.34	164.00	1.00	6.00	Q6

Cronbach Coefficient Alpha	
Variables	**Alpha**
Raw	0.545
Standardized	0.475

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	**Raw Variables**		**Standardized Variables**		**Label**
	Correlation with Total	**Alpha**	**Correlation with Total**	**Alpha**	
Q1	0.532	0.355	0.505	0.271	Q1
Q2	0.342	0.473	0.309	0.390	Q2
Q3	-0.339	0.686	-0.382	0.708	Q3
Q4	0.326	0.494	0.282	0.405	Q4
Q5	0.299	0.495	0.339	0.373	Q5
Q6	0.595	0.352	0.591	0.214	Q6

Pearson Correlation Coefficients, N = 40 Prob > |r| under H0: Rho=0

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**
Q1	1.000	0.546 0.000	-0.097 0.550	0.241 0.133	0.180 0.266	0.406 0.009
Q2	0.546 0.000	1.000	-0.137 0.399	0.082 0.617	0.004 0.982	0.339 0.032
Q3	-0.097 0.550	-0.137 0.399	1.000	-0.534 0.000	-0.125 0.443	-0.405 0.010
Q4	0.241 0.133	0.082 0.617	-0.534 0.000	1.000	0.356 0.024	0.622 <.0001
Q5	0.180 0.266	0.004 0.982	-0.125 0.443	0.356 0.024	1.000	0.489 0.001
Q6	0.406 0.009	0.339 0.032	-0.405 0.010	0.622 <.0001	0.489 0.001	1.000

Trust Scale IRR - Post Training

The CORR Procedure

Simple Statistics							
Variable	**N**	**Mean**	**Std Dev**	**Sum**	**Min.**	**Max.**	**Label**
Q1	40	3.18	1.52	127.00	1.00	7.00	Q1
Q2	40	5.03	1.39	201.00	1.00	7.00	Q2
Q3	40	4.13	1.09	165.00	1.00	7.00	Q3
Q4	40	4.48	0.85	179.00	3.00	6.00	Q4
Q5	40	3.48	1.36	139.00	1.00	5.00	Q5
Q6	40	4.15	1.33	166.00	1.00	7.00	Q6

Cronbach Coefficient Alpha	
Variables	**Alpha**
Raw	0.473
Standardized	0.467

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	**Raw Variables**		**Standardized Variables**		**Label**
	Correlation with Total	**Alpha**	**Correlation with Total**	**Alpha**	
Q1	0.335	0.364	0.326	0.369	Q1
Q2	0.263	0.413	0.245	0.415	Q2
Q3	-0.252	0.628	-0.252	0.652	Q3
Q4	0.450	0.359	0.437	0.301	Q4
Q5	0.193	0.454	0.185	0.448	Q5
Q6	0.559	0.221	0.604	0.190	Q6

Pearson Correlation Coefficients, N = 40 **Prob > |r| under H0: Rho=0**

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**
Q1	1.000	0.339 0.032	-0.169 0.299	0.273 0.089	0.145 0.371	0.279 0.082
Q2	0.339 0.032	1.000	-0.358 0.023	0.295 0.064	-0.020 0.902	0.415 0.008
Q3	-0.169 0.299	-0.358 0.023	1.000	-0.177 0.275	0.097 0.550	-0.208 0.199
Q4	0.273 0.089	0.295 0.064	-0.177 0.275	1.000	0.022 0.894	0.708 <.0001
Q5	0.145 0.371	-0.020 0.902	0.097 0.550	0.022 0.894	1.000	0.272 0.090
Q6	0.279 0.082	0.415 0.008	-0.208 0.199	0.708 <.0001	0.272 0.090	1.000

Trust Scale IRR - Post Drive

The CORR Procedure

Simple Statistics							
Variable	**N**	**Mean**	**Std Dev**	**Sum**	**Min.**	**Max.**	**Label**
Q1	40	4.43	1.60	177.00	1.00	6.00	Q1
Q2	40	5.30	1.24	212.00	2.00	7.00	Q2
Q3	40	3.70	1.07	148.00	1.00	6.00	Q3
Q4	40	4.95	1.08	198.00	2.00	7.00	Q4
Q5	40	4.95	1.01	198.00	2.00	7.00	Q5
Q6	40	4.75	1.15	190.00	1.00	7.00	Q6

Cronbach Coefficient Alpha	
Variables	**Alpha**
Raw	0.706
Standardized	0.705

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variables	**Raw Variables**		**Standardized Variables**		Labels
	Correlation with Total	**Alpha**	**Correlation with Total**	**Alpha**	
Q1	0.455	0.671	0.448	0.662	Q1
Q2	0.582	0.618	0.584	0.618	Q2
Q3	-0.182	0.816	-0.162	0.828	Q3
Q4	0.670	0.599	0.649	0.595	Q4
Q5	0.457	0.664	0.465	0.657	Q5
Q6	0.812	0.545	0.796	0.542	Q6

Pearson Correlation Coefficients, N = 40 **Prob > |r| under H0: Rho=0**

	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**
Q1	1.000	0.359 0.023	-0.269 0.093	0.500 0.001	0.267 0.096	0.603 <.0001
Q2	0.359 0.023	1.000	-0.124 0.447	0.600 <.0001	0.318 0.046	0.681 <.0001
Q3	-0.269 0.093	-0.124 0.447	1.000	-0.146 0.368	0.105 0.521	-0.188 0.245
Q4	0.500 0.001	0.600 <.0001	-0.146 0.368	1.000	0.301 0.059	0.751 <.0001
Q5	0.267 0.096	0.318 0.046	0.105 0.521	0.301 0.059	1.000	0.518 0.001
Q6	0.603 <.0001	0.681 <.0001	-0.188 0.245	0.751 <.0001	0.518 0.001	1.000

Appendix G. A Naturalistic Evaluation of Driver Behavior Using Driving Automation Systems - IRB Approval 1 Original Data Collection

VIRGINIA TECH.

Office of Research Compliance
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Blacksburg, Virginia 24061
540/231-3732 Fax 540/231-0959
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MEMORANDUM

DATE: July 6, 2018

TO: Michael Mollenhauer, Alexandria Marie Noble, Melissa Hulse, Zachary Richard Doerzaph, Pamela Marie Murray-Tuite, Charlie Klauer, Kevin Patrick Heaslip II, Tom Dingus, Nicholas Norris Britten, Marty Miller, et. al.

FROM: Virginia Tech Institutional Review Board (FWA00000572, expires January 29, 2021)

PROTOCOL TITLE: VTTI- VCC L2 Naturalistic Driving Study

IRB NUMBER: 16-309

Effective July 5, 2018, the Virginia Tech Institution Review Board (IRB) approved the Amendment request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

http://www.irb.vt.edu/pages/responsibilities.htm

(Please review responsibilities before the commencement of your research.)

PROTOCOL INFORMATION:

Approved As:	**Full Review**
Protocol Approval Date:	**April 9, 2018**
Protocol Expiration Date:	**April 8, 2019**
Continuing Review Due Date*:	**March 25, 2019**

*Date a Continuing Review application is due to the IRB office if human subject activities covered under this protocol, including data analysis, are to continue beyond the Protocol Expiration Date.

FEDERALLY FUNDED RESEARCH REQUIREMENTS:

Per federal regulations, 45 CFR 46.103(f), the IRB is required to compare all federally funded grant proposals/work statements to the IRB protocol(s) which cover the human research activities included in the proposal / work statement before funds are released. Note that this requirement does not apply to Exempt and Interim IRB protocols, or grants for which VT is not the primary awardee.

The table on the following page indicates whether grant proposals are related to this IRB protocol, and which of the listed proposals, if any, have been compared to this IRB protocol, if required.

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Appendix H. A Naturalistic Evaluation of Driver Behavior Using Driving Automation Systems - IRB Approval Datamining

VIRGINIA TECH

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MEMORANDUM

DATE:	January 11, 2019
TO:	Charlie Klauer, Gayatri Ankem, Stephanie Ann Baker, Peter Allen Baynes, Youjia Fang, Feng Guo, Julie A McClafferty, Miguel A Perez, Jessica Renee Rardin, Alexandria Marie Noble, et. al.
FROM:	Virginia Tech Institutional Review Board (FWA00000572, expires January 29, 2021)
PROTOCOL TITLE:	Data mining of VCC50 study
IRB NUMBER:	**17-1026**

Effective January 10, 2019, the Virginia Tech Institution Review Board (IRB) approved the Amendment request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before the commencement of your research.)

PROTOCOL INFORMATION:

Approved As:	**Expedited, under 45 CFR 46.110 category(ies) 5**
Protocol Approval Date:	**May 27, 2018**
Protocol Expiration Date:	**May 26, 2019**
Continuing Review Due Date*:	**May 12, 2019**

*Date a Continuing Review application is due to the IRB office if human subject activities covered under this protocol, including data analysis, are to continue beyond the Protocol Expiration Date.

FEDERALLY FUNDED RESEARCH REQUIREMENTS:

Per federal regulations, 45 CFR 46.103(f), the IRB is required to compare all federally funded grant proposals/work statements to the IRB protocol(s) which cover the human research activities included in the proposal / work statement before funds are released. Note that this requirement does not apply to Exempt and Interim IRB protocols, or grants for which VT is not the primary awardee.

The table on the following page indicates whether grant proposals are related to this IRB protocol, and which of the listed proposals, if any, have been compared to this IRB protocol, if required.

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Appendix I. A Naturalistic Evaluation of Driver Behavior Using Driving Automation Systems - Algorithm Limitations

Background

In order to identify the status/presence of the icons used that are used to indicate the state of the driver assistance systems as machine vision algorithm was developed. The algorithm is based on image classification using deep neural networks, specifically residual neural network (ResNET) architecture. One model was developed for each type of vehicle in the study fleet.

Limitations

Conditions that may result in false positives:

1. Direct sun light or street lights (at night) makes recognition very unstable
2. Certain instrument panel materials had highly reflective surfaces which required a larger training dataset to eliminate this extra video noise.
3. Smaller icons give higher false rates.
4. White/Grayscale icons (colored icons significantly decrease false positive rate)
5. For models we used near square regions with icons give better recognition rate than long rectangular ones larger than 1:4

Additional Considerations

Algorithm development did not consider system design characteristics or operator choice in the development of the algorithm. A small number of the vehicles in the sample deactivate (on the display) the lateral control systems when turn signals are activated. While this makes intuitive sense, upon the completion of the lane change, the lateral control system reactivates automatically, without operator input. The result of this is noisy data that is a result of system design characteristic, not of operator decision. Unfortunately this feature was not specified in the manual and could not be accounted for in the initial development of the algorithm by coding turn signal status as well, for example.

Excluded Vehicles

Vehicle	Reason
429213	Model year had limited functionality and different panel icons from others
429038	Could not distinguish between icon states (due to lack of color)
428939	Could not distinguish between icon states (due to lack of color)
428941	All trips have failed timestamps

429119	Icons are too small to be processed camera too far
429121	Icons are too small to be processed camera too far
395814	Skipped by PI decision
428843	Skipped by PI decision
428861	Skipped by PI decision
429021	Skipped by PI decision

Appendix J. Defining on Road Glance Locations

Glance Location	On/Off Driving	Description
Cell Phone (electronic communications device)	Off-Driving	Any glance at a cell phone or other electronic communications device (e.g., BlackBerry) or associated items (e.g., power cord, charger, etc.), no matter where they are located.
Center Stack	Off-Driving	Any glance to the vehicle's center stack (the vertical portion), usually housing the radio, climate control, etc. Not to be confused with center console (cup holder area between driver and passenger).
Eyes Closed	Off-Driving	Any time that the participant's eyes are closed outside of normal blinking (e.g., the participant is falling asleep). As a rule of thumb, if the eyes are closed for five or more syncs (0.5s) during a slow blink, it is coded as Eyes Closed.
Forward	On-Driving	Any glance in the direction of the vehicle's travel. Note that when the vehicle is turning, these glances may not be directed directly forward but towards the vehicle's predicted or intended heading.
Instrument Cluster	On-Driving	Any glance to the instrument cluster underneath the dashboard. This includes glances to the speedometer, control stalks, and steering wheel. Note that clusters may be in different places (e.g., driver-centerline versus vehicle-centerline), but they will be included in this category regardless of location. In the case of trucks this might include an area that 'wraps' around the driver.
Interior Object	Off-Driving	Any glance to an identifiable object in the vehicle other than an electronic communications device or iPod. These objects include personal items brought in by the participant (e.g., purse, food, papers), any part of their body that they may look at (e.g., hand, ends of hair), other electronic devices (e.g., laptop), and also original equipment manufacturer-installed devices that don't fall into other categories (e.g., door lock, seat belt, window and seat controls). Glances to the center console (cup holder area between passenger seat and driver seat) are also included in this category. The object does not need to be in the camera view for a specific frame to be coded with this category. If it is clear from surrounding video that the participant is looking at the object, this category may be used. This category can be used regardless of whether the participant's hands are visible.
iPod (or similar)	Off-Driving	Any glance at an iPod or other personal digital music device, no matter where it is located

Glance Location	On/Off Driving	Description
Left Mirror	On-Driving	Any glance to the left side mirror.
Left Window	Off-Driving	Any glance out the left side window.
Left Windshield	Off-Driving	Any glance out the left portion of the windshield, to the left of forward (e.g., NOT looking in the direction of travel). Glances should be coded only if clear, and finite.
No Eyes Visible - Eyes Are Off-Road	N/A	Unable to determine specific glance location due to an inability to see the driver's eyes and face. However, it is clear that the participant is not looking at the roadway. Video is present, but the driver's eyes and face are not visible due to an obstruction (e.g., visor, hand), head position, or due to glare. Use this category when the eyes are not visible, you are not sure what the participant is looking at, but it is obvious that the eyes are not on the roadway.
No Eyes Visible - Glance Location Unknown	N/A	Unable to complete glance analysis due to an inability to see the driver's eyes and face. Video data are present, but the driver's eyes and face are not visible due to an obstruction (e.g., visor, hand), or due to glare. This category was used when there was no way to tell whether the participant's eyes are on or off the road.
No Video	N/A	Unable to complete eye glance analysis because the face video view is unavailable. Used only when this condition is intermittent and surrounding syncs can be completed.
Other	Off-Driving	Any glance that cannot be categorized using the above codes (e.g., specific built-in vehicle features).
Over-The-Shoulder (left or right)	Off-Driving	Any glance over either of the participant's shoulders. In general, this will require the eyes to pass the B-pillar, but the eyes may not be visible.
Passenger	Off-Driving	Any glance to a passenger, whether in front seat or rear seat of vehicle. Context is used (e.g., they are conversing) in order to determine this in some situations.
Rearview Mirror	On-Driving	Any glance to the rearview mirror or equipment located around it. This category does not include any glances to the Center Stack.
Right Mirror	On-Driving	Any glance to the right side mirror.
Right Window	Off-Driving	Any glance out the right side window.

Glance Location	On/Off Driving	Description
Right Windshield	Off-Driving	Any glance out the right portion of the windshield, to the right of forward (e.g., NOT looking in the direction of travel). Glances should be coded only if clear, and finite.

Appendix K. Behavioral Adaptation with Driving Automation at Early Exposure - IRB Approval

VIRGINIA TECH.

Division of Scholarly Integrity and Research Compliance
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MEMORANDUM

DATE: November 7, 2019

TO: Charlie Klauer, Stephanie Ann Baker, Marissa Turturici, Alexandria Marie Noble, Myra Blanco, Feng Guo, Shu Han, Jonathan Richard Atwood

FROM: Virginia Tech Institutional Review Board (FWA00000572, expires January 29, 2021)

PROTOCOL TITLE: Exploring Driver Adaptation to Lower Levels of Automation using Existing Naturalistic Driving Data

IRB NUMBER: **19-549**

Effective November 7, 2019, the Virginia Tech Institution Review Board (IRB) approved the New Application request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

PROTOCOL INFORMATION:

Approved As:	**Expedited, under 45 CFR 46.110 category(ies) 5**
Protocol Approval Date:	**November 7, 2019**
Progress Review Date:	**November 6, 2020**

ASSOCIATED FUNDING:

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

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Appendix L. Participant Driving Exposure

PID	Overall Driving		High Speed Exposure (Hours)		High Speed Exposure (Miles)	
	Hours	Miles	L2 Available	L2 Active	L2 Available	L2 Active
1	65.86	2,025.46	17.35	5.99	959.64	402.25
2	52.64	1,660.70	6.60	9.03	371.62	623.97
3	69.50	2,591.09	20.57	9.31	1,179.11	573.60
4	56.84	1,663.74	2.71	8.40	132.84	539.03
5	63.37	1,896.25	4.27	15.23	232.97	1,004.22
6	95.16	2,267.04	8.85	16.75	488.09	1,076.49
7	47.72	1,468.93	9.84	4.18	523.79	264.23
8	35.82	1,436.10	2.32	14.14	122.05	956.09
9	94.12	2,634.07	11.75	9.51	676.69	562.51
10	101.82	2,737.66	13.62	14.64	790.99	999.50
11	59.19	1,974.16	10.48	11.10	610.94	678.85
12	74.82	2,224.09	5.01	22.17	250.05	1,413.07
13	33.42	782.07	2.84	4.39	167.37	303.32
14	44.38	1,027.37	9.29	1.40	543.44	86.02
15	42.27	1,402.34	6.17	6.05	327.22	410.96
16	47.08	1,857.16	7.05	16.81	370.92	1,069.51
17	77.91	2,250.46	13.21	9.96	792.12	709.21
18	61.91	1,715.62	4.67	14.49	232.23	857.92
19	145.80	3,421.49	18.53	6.38	966.58	425.98
20	98.02	3,043.00	19.85	16.83	1,211.07	1,069.57
21	40.66	1,518.12	4.35	13.70	236.18	909.65
22	81.32	2,291.12	11.94	11.78	641.43	767.04
23	14.30	482.46	2.61	2.74	155.33	187.87
Mean:	65.39	1,929.15	9.30	10.65	520.98	690.91
SD:	28.70	701.33	5.75	5.32	334.86	340.02
SE:	5.98	146.24	1.20	1.11	69.82	70.90
Min:	14.30	482.46	2.32	1.40	122.05	86.02
Max:	145.80	3,421.49	20.57	22.17	1,211.07	1,413.07

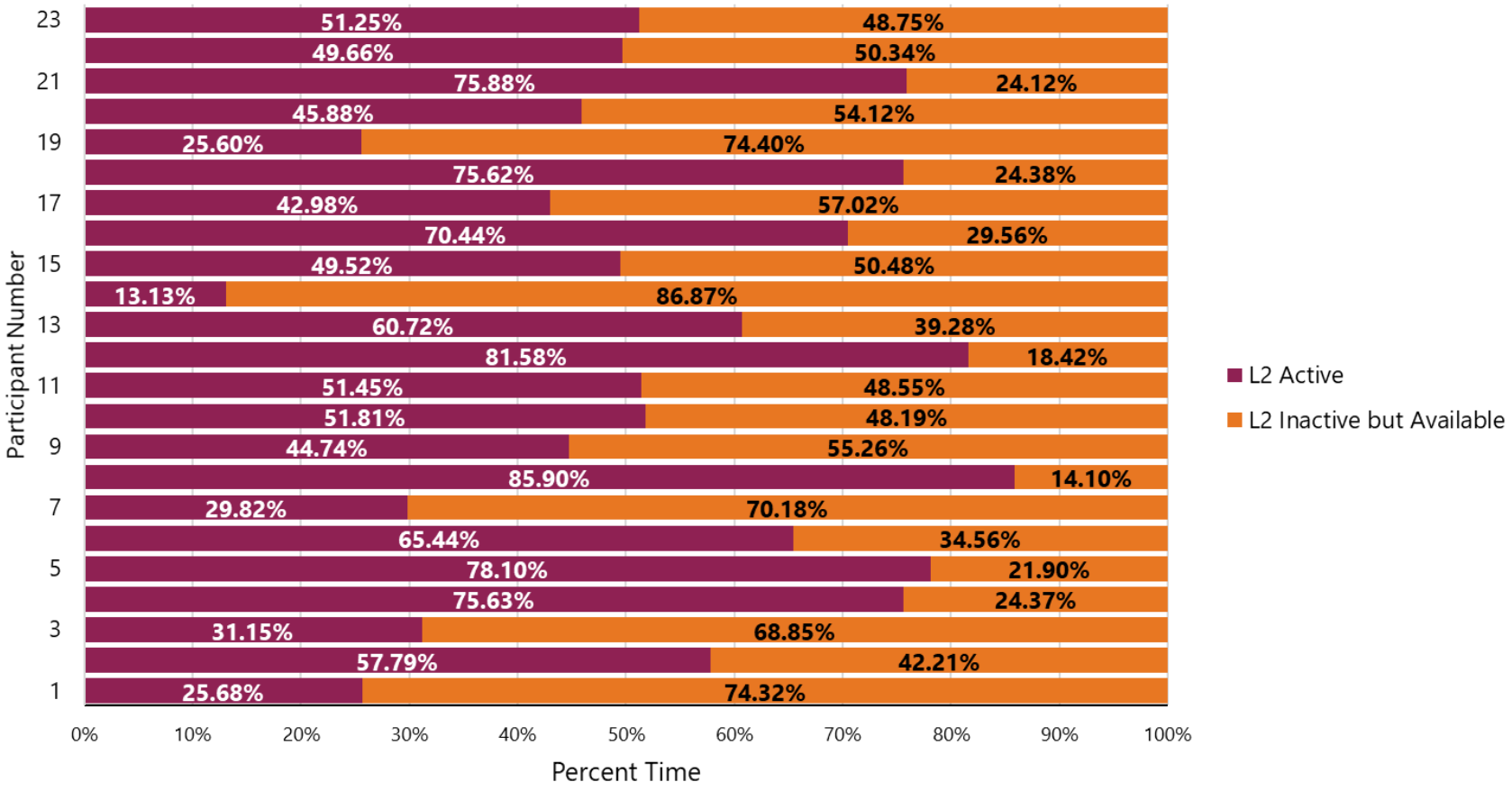


Figure 30. Participant use of L2 systems as a percentage of time at speeds greater than or equal to 40 miles per hour while enrolled in the study.

Appendix M. Minimum Time Gap Power Solutions and Power Analyses

Model solutions (β, SE) are computed results using PROC GLIMMIX in SAS® 9.4; power is computed using PASS11.

Sample Size (N):	50,943
SE Residual (S):	0.002
Estimate Residual (ES):	0.313
α:	0.05

Effect	Automation	Phase	β	SE	Power
Intercept			0.097	0.016	
Automation	ON		-0.016	0.013	1
Automation	OFF		0	.	
Phase		PHASE 1	0.015	0.021	1
Phase		PHASE 2	-0.017	0.020	1
Phase		PHASE 3	0	.	
Automation×Phase	ON	PHASE 1	0.047	0.018	1
Automation×Phase	ON	PHASE 2	0.027	0.017	1
Automation×Phase	ON	PHASE 3	0	.	
Automation×Phase	OFF	PHASE 1	0	.	
Automation×Phase	OFF	PHASE 2	0	.	
Automation×Phase	OFF	PHASE 3	0	.	

N is the size of the sample drawn from the population. To conserve resources, it should be small.
β is the slope estimate for each effect.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Appendix N. Mean Time Gap Solutions and Power Analyses

Model solutions (β, SE) are computed results using PROC GLIMMIX in SAS® 9.4; power is computed using PASS11.

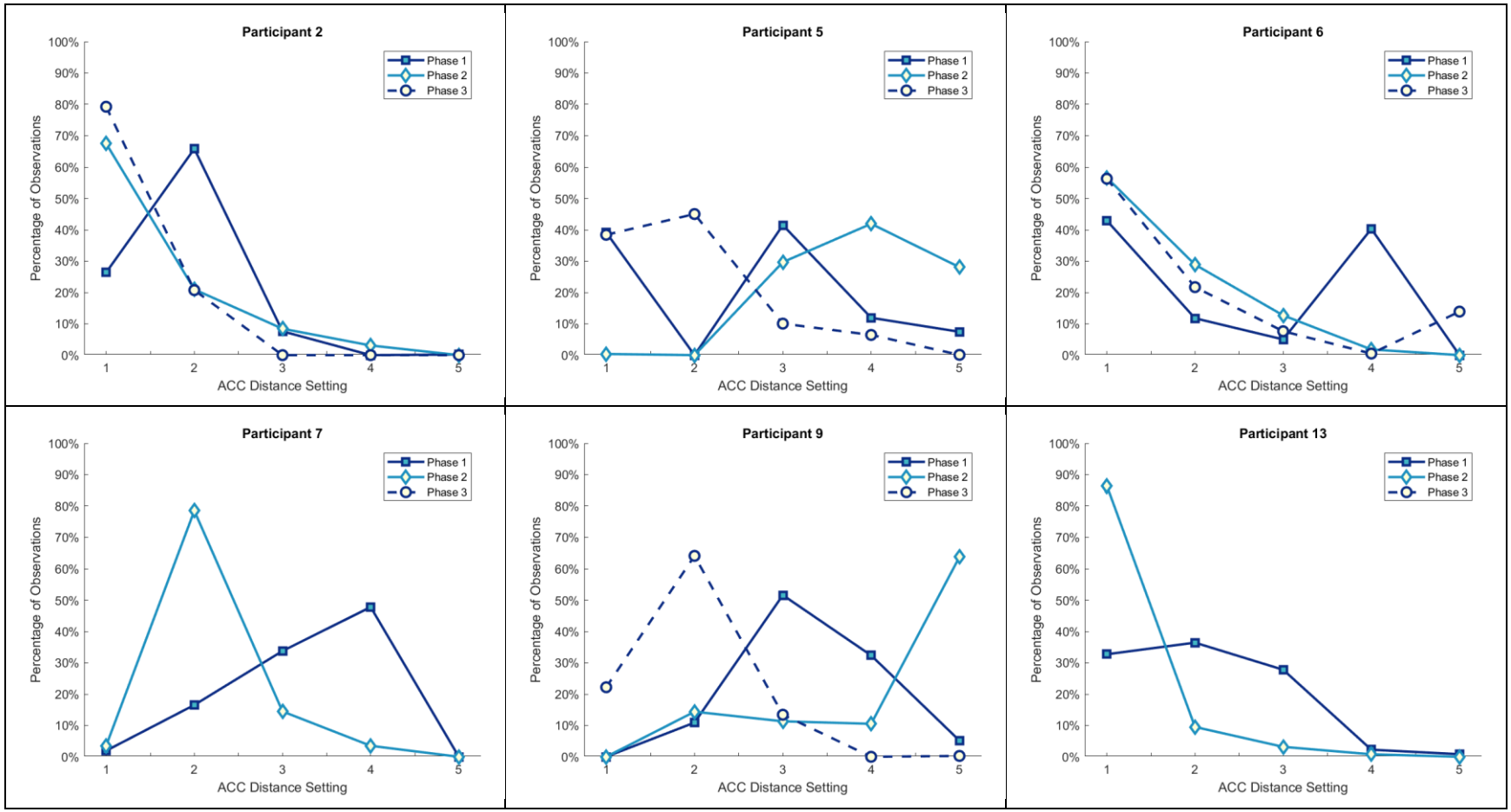
Sample Size (N):	50,943
SE Residual (S):	0.002
Estimate Residual (ES):	0.294
α:	0.05

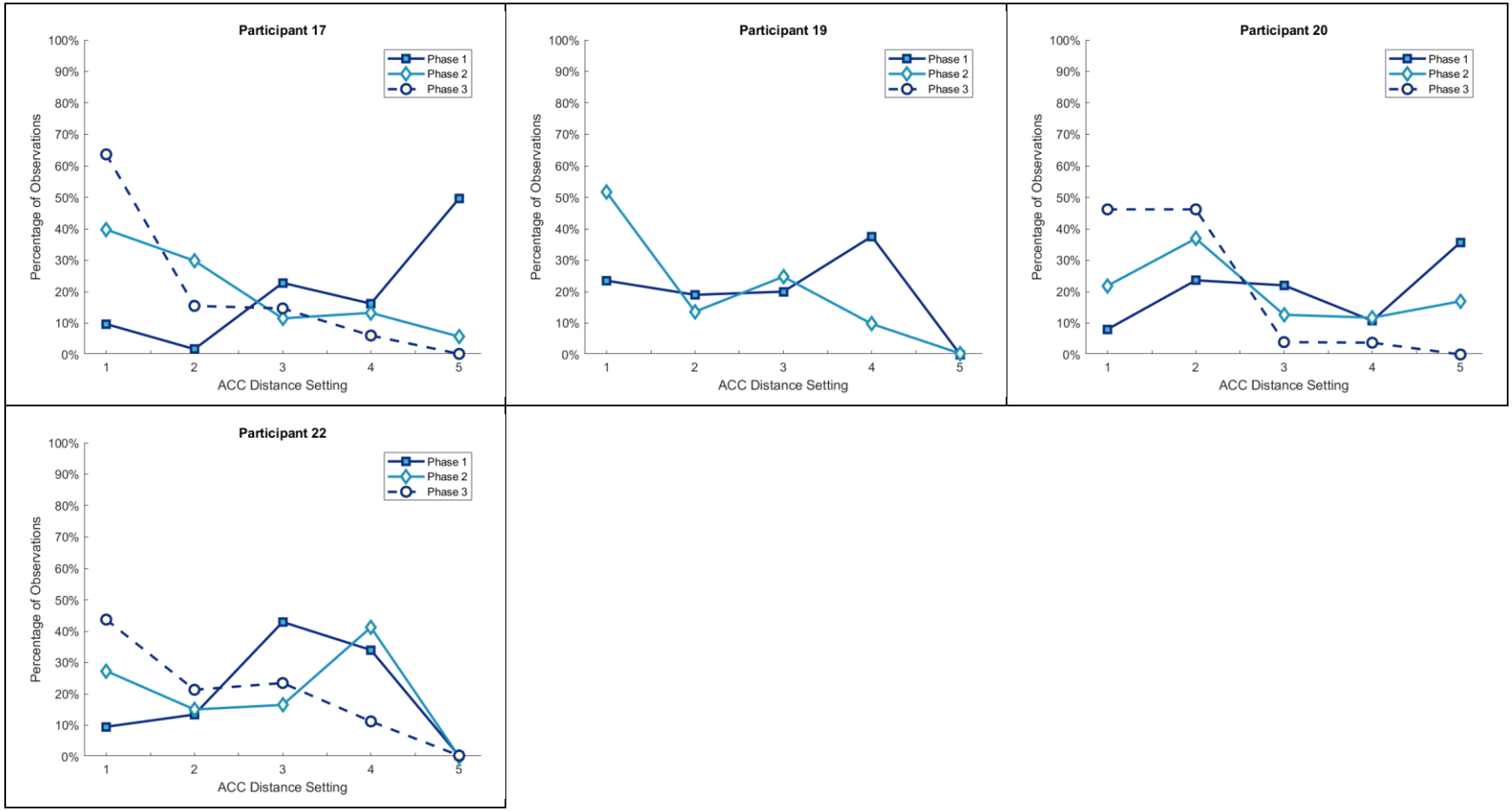
Effect	Automation	Phase	β	SE	Power
Intercept			0.465	0.016	1
Automation	ON		-0.040	0.013	1
Automation	OFF		0	.	
Phase		PHASE 1	-0.028	0.020	1
Phase		PHASE 2	-0.047	0.019	1
Phase		PHASE 3	0	.	
Automation×Phase	ON	PHASE 1	0.070	0.017	1
Automation×Phase	ON	PHASE 2	0.053	0.017	1
Automation×Phase	ON	PHASE 3	0	.	
Automation×Phase	OFF	PHASE 1	0	.	
Automation×Phase	OFF	PHASE 2	0	.	
Automation×Phase	OFF	PHASE 3	0	.	

N is the size of the sample drawn from the population. To conserve resources, it should be small.
β is the slope estimate for each effect.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

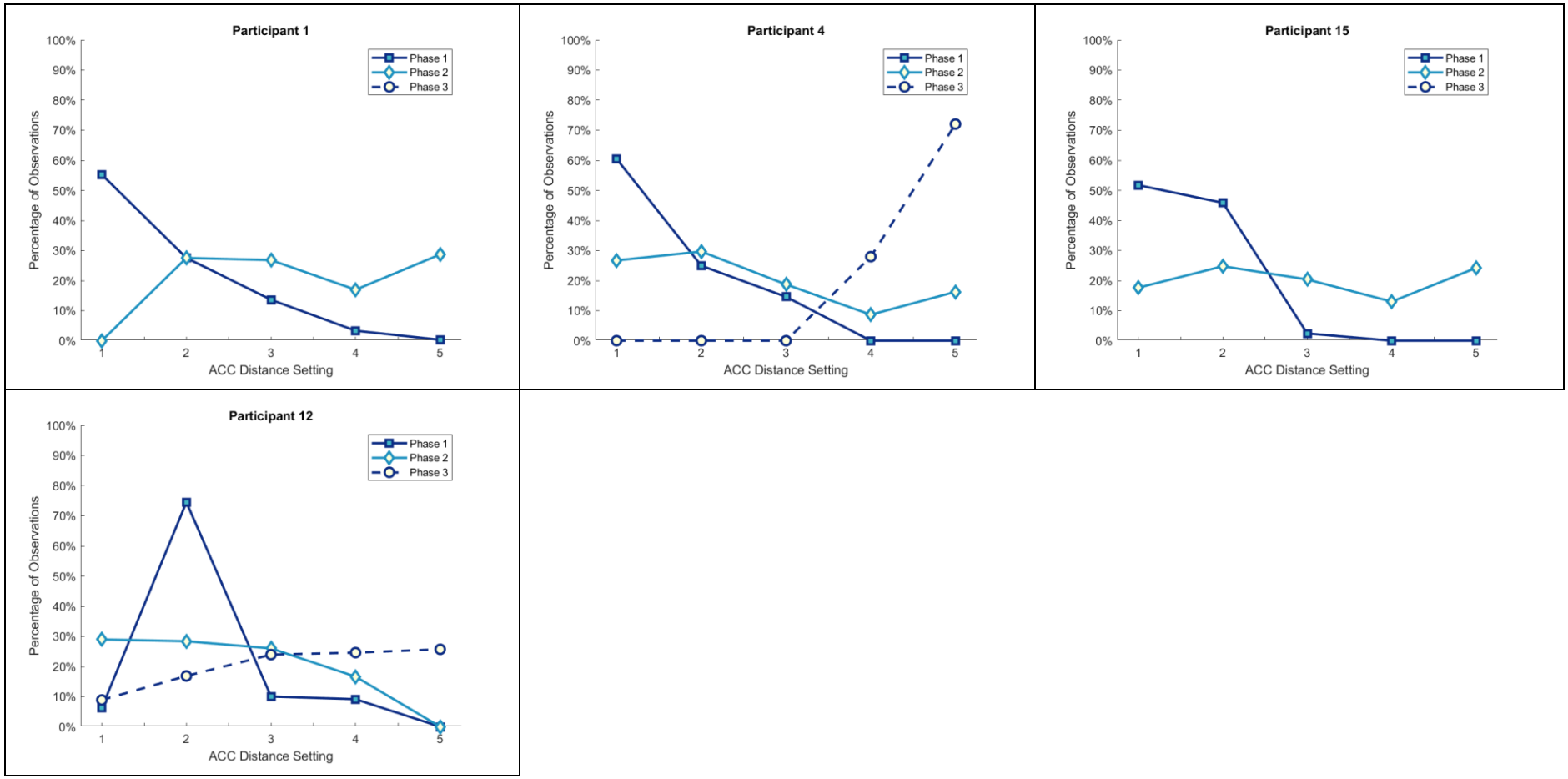
Appendix O. ACC Distance Settings over Time by Participant

Moves to a <u>Lower</u> ACC Distance Setting

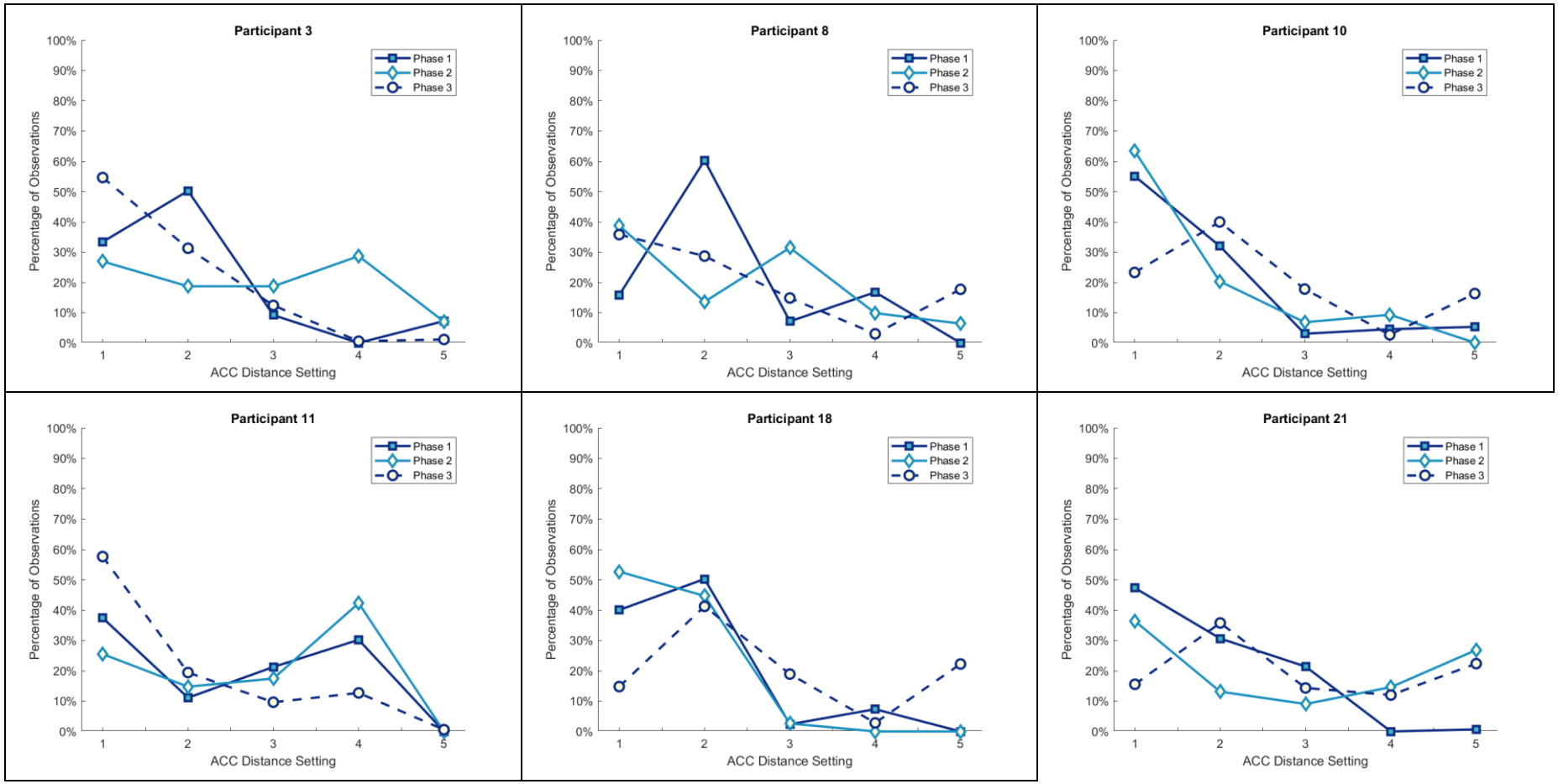



Participant 17
Participant 19
Participant 20
Participant 22
Phase 1
Phase 2
Phase 3
Percentage of Observations
ACC Distance Setting
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1
2
3
4
5

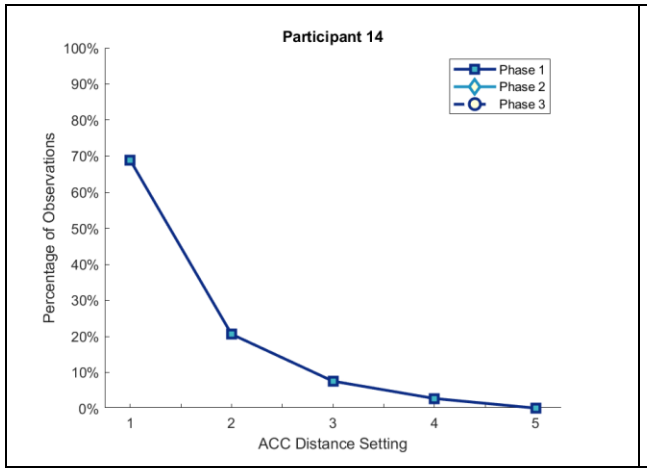
Moves to a <u>Higher</u> ACC Distance Setting

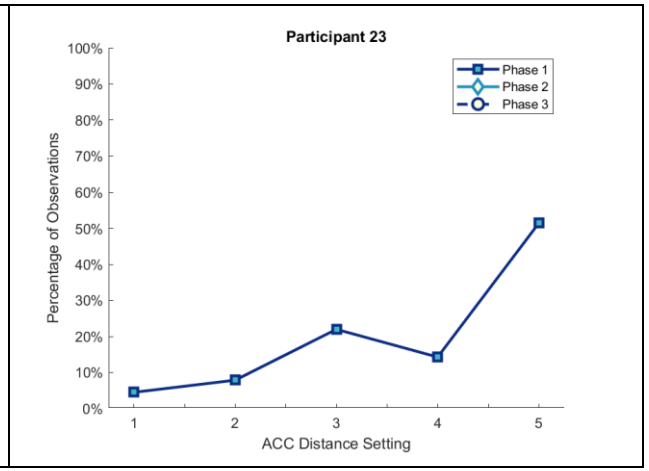


Generally consistent or no apparent change in use



One Exposure Phase





Appendix P. Eyes off Road Model Solutions and Power Analyses

Model solutions (β, SE) are computed results using PROC GLIMMIX in SAS® 9.4; power is computed using PASS11.

Total Eyes off Road Time (TEORT)

Sample Size (N):	556
SE Residual (S):	0.3677
Estimate Residual (ES):	5.9727
α:	0.05

Effect	Automation	Phase	β	SE	Power
Intercept			2.445	0.409	
Automation	ON		0.773	0.486	1
Automation	OFF		0	.	
Phase		PHASE 1	-0.142	0.418	0.96
Phase		PHASE 2	-0.210	0.433	1
Phase		PHASE 3	0	.	
Automation×Phase	ON	PHASE 1	-0.355	0.572	1
Automation×Phase	ON	PHASE 2	-0.034	0.601	0.24
Automation×Phase	ON	PHASE 3	0	.	
Automation×Phase	OFF	PHASE 1	0	.	
Automation×Phase	OFF	PHASE 2	0	.	
Automation×Phase	OFF	PHASE 3	0	.	

N is the size of the sample drawn from the population. To conserve resources, it should be small.
β is the slope estimate for each effect.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Mean Glance off Road

Sample Size (N):	556
SE Residual (S):	0.015
Estimate Residual (ES):	0.251
α:	0.05

Effect	Automation	Phase	β	SE	Power
Intercept			0.583	0.076	
Automation	ON		0.193	0.100	1
Automation	OFF		0	.	
Phase		PHASE 1	0.013	0.085	0.23
Phase		PHASE 2	0.002	0.088	0.06
Phase		PHASE 3	0	.	
Automation×Phase	ON	PHASE 1	-0.077	0.117	1
Automation×Phase	ON	PHASE 2	-0.075	0.123	1
Automation×Phase	ON	PHASE 3	0	.	
Automation×Phase	OFF	PHASE 1	0	.	
Automation×Phase	OFF	PHASE 2	0	.	
Automation×Phase	OFF	PHASE 3	0	.	

N is the size of the sample drawn from the population. To conserve resources, it should be small.
β is the slope estimate for each effect.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Single Longest Glance

Sample Size (N):	556
SE Residual (S):	0.053
Estimate Residual (ES):	0.858
α:	0.05

Effect	Automation	Phase	β	SE	Power
Intercept			0.963	0.145	
Automation	ON		0.339	0.184	1
Automation	OFF		0	.	
Phase		PHASE 1	-0.079	0.158	1
Phase		PHASE 2	-0.118	0.164	1
Phase		PHASE 3	0	.	
Automation×Phase	ON	PHASE 1	-0.136	0.217	1
Automation×Phase	ON	PHASE 2	-0.012	0.228	0.18
Automation×Phase	ON	PHASE 3	0	.	
Automation×Phase	OFF	PHASE 1	0	.	
Automation×Phase	OFF	PHASE 2	0	.	
Automation×Phase	OFF	PHASE 3	0	.	

N is the size of the sample drawn from the population. To conserve resources, it should be small.
β is the slope estimate for each effect.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Number of Off Road Glances

Sample Size (N):	556
Baseline Rate:	3.42
Mean Obsv. Dur:	14.92
α	0.05
ϕ:	1

Effect	Automation	Phase	β	SE	e^{β}	R^2	Power
Intercept			1.226	0.104	3.41		
Automation	ON		-0.023	0.103	0.98	0.139	0.35
Automation	OFF		0	.	1.00	0.139	
Phase		PHASE 1	-0.099	0.091	0.91	0.001	1
Phase		PHASE 2	-0.060	0.093	0.94	0.001	1
Phase		PHASE 3	0	.	1.00		
Automation×Phase	ON	PHASE 1	0.073	0.123	1.08	0.458	1
Automation×Phase	ON	PHASE 2	0.008	0.129	1.01	0.602	0.08
Automation×Phase	ON	PHASE 3	0	.	1.00		
Automation×Phase	OFF	PHASE 1	0	.	1.00		
Automation×Phase	OFF	PHASE 2	0	.	1.00		
Automation×Phase	OFF	PHASE 3	0	.	1.00		

N is the size of the sample drawn from the population.
β is the estimate for each effect.
e^{β} is the response rate for each effect due to a unit change in X_i
ϕ is the over-dispersion parameter used when the Poisson model does not fit.
R^2 is the R-squared achieved when X_i is regressed on the other covariates.
α is the probability of rejecting $Exp(B_i)/Exp(B_0)$ is one.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Appendix Q. Instrument Panel Glance Model Solutions and Power Analyses

Model solutions (β, SE) are computed results using PROC GLIMMIX in SAS® 9.4; power is computed using PASS11.

Total Glance Duration to Instrument Panel

Sample Size (N):	556
SE Residual (S):	0.039
Estimate Residual (ES):	0.641
α:	0.05

Effect	Automation	Phase	β	SE	Power
Intercept			0.361	0.134	
Automation	ON		0.120	0.159	1
Automation	OFF		0	.	
Phase		PHASE 1	0.090	0.137	1
Phase		PHASE 2	-0.071	0.142	0.99
Phase		PHASE 3	0	.	
Automation×Phase	ON	PHASE 1	-0.002	0.188	0.05
Automation×Phase	ON	PHASE 2	0.066	0.197	1
Automation×Phase	ON	PHASE 3	0	.	
Automation×Phase	OFF	PHASE 1	0	.	
Automation×Phase	OFF	PHASE 2	0	.	
Automation×Phase	OFF	PHASE 3	0	.	

N is the size of the sample drawn from the population. To conserve resources, it should be small.
β is the slope estimate for each effect.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Mean Glance Duration to Instrument Panel

Sample Size (N):	556
SE Residual (S):	0.008
Estimate Residual (ES):	0.130
α:	0.05

Effect	Automation	Phase	β	SE	Power
Intercept			0.182	0.058	
Automation	ON		0.063	0.072	1
Automation	OFF		0	.	
Phase		PHASE 1	0.060	0.061	1
Phase		PHASE 2	-0.008	0.064	0.23
Phase		PHASE 3	0	.	
Automation×Phase	ON	PHASE 1	0.032	0.084	1
Automation×Phase	ON	PHASE 2	0.029	0.089	1
Automation×Phase	ON	PHASE 3	0	.	
Automation×Phase	OFF	PHASE 1	0	.	
Automation×Phase	OFF	PHASE 2	0	.	
Automation×Phase	OFF	PHASE 3	0	.	

N is the size of the sample drawn from the population. To conserve resources, it should be small.
β is the slope estimate for each effect.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Single Longest Glance to Instrument Panel

Sample Size (N):	556
SE Residual (S):	0.012
Estimate Residual (ES):	0.201
α:	0.05

Effect	Automation	Phase	β	SE	Power
Intercept			0.242	0.073	
Automation	ON		0.054	0.089	1
Automation	OFF		0	.	
Phase		PHASE 1	0.054	0.076	1
Phase		PHASE 2	-0.045	0.079	1
Phase		PHASE 3	0	.	
Automation×Phase	ON	PHASE 1	0.035	0.105	1
Automation×Phase	ON	PHASE 2	0.073	0.110	1
Automation×Phase	ON	PHASE 3	0	.	
Automation×Phase	OFF	PHASE 1	0	.	
Automation×Phase	OFF	PHASE 2	0	.	
Automation×Phase	OFF	PHASE 3	0	.	

N is the size of the sample drawn from the population. To conserve resources, it should be small.
β is the slope estimate for each effect.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Number of Glances to the Instrument Panel

Sample Size (N):	556
Baseline Rate:	0.7
Mean Obsv. Dur:	14.92
α:	0.05
ϕ:	1

Effect	Automation	Phase	β	SE	e^{β}	R^2	Power
Intercept			-0.604	0.223	0.55		
Automation	ON		0.112	0.235	1.12	0.139	0.98
Automation	OFF		0	.	1.00	0.139	
Phase		PHASE 1	0.027	0.209	1.03	0.001	0.2
Phase		PHASE 2	-0.227	0.225	0.80	0.001	1
Phase		PHASE 3	0	.	1.00		
Automation×Phase	ON	PHASE 1	0.154	0.275	1.17	0.458	0.99
Automation×Phase	ON	PHASE 2	0.176	0.299	1.19	0.602	0.99
Automation×Phase	ON	PHASE 3	0	.	1.00		
Automation×Phase	OFF	PHASE 1	0	.	1.00		
Automation×Phase	OFF	PHASE 2	0	.	1.00		
Automation×Phase	OFF	PHASE 3	0	.	1.00		

N is the size of the sample drawn from the population.
β is the estimate for each effect.
e^{β} is the response rate for each effect due to a unit change in X_i
ϕ is the over-dispersion parameter used when the Poisson model does not fit.
R^2 is the R-squared achieved when X_i is regressed on the other covariates.
α is the probability of rejecting $Exp(B_i)/Exp(B_0)$ is one.
Power is the probability of rejecting a false null hypothesis. It should be close to one.

Appendix R. Secondary Task Logistic Regression Output and Odds Ratios

Automation Inactive but Available is the reference group

	PHASE	Est	SE	DF	t Value	Pr > |t|	OR	LL	UL
Any Task	PHASE 1	0.04	0.27	528	0.13	0.894	1.037	0.61	1.762
	PHASE 2	-0.23	0.34	528	-0.68	0.499	0.795	0.408	1.548
	PHASE 3	-0.27	0.45	528	-0.61	0.544	0.762	0.316	1.836
All Cellphone	PHASE 1	-0.20	0.44	528	-0.46	0.647	0.817	0.343	1.944
	PHASE 2	-0.10	0.44	528	-0.22	0.825	0.906	0.379	2.165
	PHASE 3	-0.71	0.70	528	-1.02	0.310	0.492	0.125	1.938
Visual-Manual Cellphone	PHASE 1	-0.56	0.56	528	-1	0.316	0.571	0.191	1.709
	PHASE 2	0.47	0.57	528	0.83	0.405	1.606	0.525	4.907
	PHASE 3	1.52	1.16	528	1.31	0.191	4.571	0.468	44.611
Talking [a]	PHASE 1	0.53	0.64	550	0.83	0.409	1.695	0.483	5.952
	PHASE 2	-0.87	0.62	550	-1.4	0.162	0.42	0.125	1.418
	PHASE 3	-13.57	336.00	550	-0.04	0.968	<0.001	<0.001	>999.9
Texting [a]	PHASE 1	12.67	576.53	550	0.02	0.983	>999.9	<0.001	Infty
	PHASE 2	0.00	658.89	550	0	1.000	1	<0.001	Infty
	PHASE 3	13.65	658.89	550	0.02	0.984	>999.9	<0.001	Infty
Dialing [a]	PHASE 1	12.67	576.53	550	0.02	0.983	>999.9	<0.001	Infty
	PHASE 2	0.00	762.13	550	0	1.000	1	<0.001	Infty
	PHASE 3	0.00	762.13	550	0	1.000	1	<0.001	Infty
Browsing	PHASE 1	-0.52	0.67	528	-0.78	0.436	0.594	0.16	2.204
	PHASE 2	0.38	0.62	528	0.61	0.544	1.456	0.432	4.901
	PHASE 3	1.17	1.19	528	0.98	0.326	3.224	0.312	33.355
Reaching Phone [a]	PHASE 1	-0.75	1.23	550	-0.61	0.540	0.47	0.042	5.277
	PHASE 2	12.01	403.78	550	0.03	0.976	>999.9	<0.001	Infty
	PHASE 3	12.65	559.49	550	0.02	0.982	>999.9	<0.001	Infty
Reaching for object in vehicle (non-cellphone) [a]	PHASE 1	13.37	576.53	550	0.02	0.982	>999.9	<0.001	Infty
	PHASE 2	13.72	665.71	550	0.02	0.984	>999.9	<0.001	Infty
	PHASE 3	-0.73	1.24	550	-0.59	0.555	0.48	0.042	5.498
External Distraction	PHASE 1	-0.47	0.66	528	-0.72	0.472	0.623	0.171	2.267
	PHASE 2	0.36	0.60	528	0.59	0.553	1.432	0.437	4.694
	PHASE 3	-0.02	0.62	528	-0.03	0.975	0.981	0.293	3.287
Passenger Interaction	PHASE 1	0.30	0.30	528	1.01	0.315	1.354	0.749	2.447
	PHASE 2	-0.42	0.35	528	-1.21	0.227	0.655	0.33	1.301
	PHASE 3	-0.21	0.59	528	-0.37	0.715	0.807	0.255	2.554
Drinking	PHASE 1	12.37	349.68	550	0.04	0.972	>999.9	<0.001	>999.9
	PHASE 2	1.12	1.16	550	0.96	0.336	3.065	0.312	30.147

	PHASE 3	-1.16	1.17	550	-0.99	0.323	0.313	0.031	3.135
Eating	PHASE 1	0.65	1.23	550	0.53	0.599	1.91	0.17	21.435
	PHASE 2	12.72	403.78	550	0.03	0.975	>999.9	<0.001	Infty
	PHASE 3	12.65	559.49	550	0.02	0.982	>999.9	<0.001	Infty
Hygiene	PHASE 1	-0.05	0.72	528	-0.06	0.950	0.956	0.232	3.935
	PHASE 2	0.00	0.73	528	0	1.000	1	0.241	4.155
	PHASE 3	0.39	0.94	528	0.41	0.681	1.472	0.232	9.317
Reading/Writing (includes tablet)									
Dancing [a]	PHASE 1	1.3553	1.1249	550	1.2	0.2288	3.878	0.426	35.34
	PHASE 2	-2.3E-14	1.4216	550	0	1	1	0.061	16.322
	PHASE 3	11.654	339.35	550	0.03	0.9726	>999.9	<0.001	>999.9

[a] Indicates conventional logistic regression was used.